

A METHODOLOGY FOR TECHNOLOGY IDENTIFICATION,
EVALUATION, AND SELECTION IN CONCEPTUAL AND
PRELIMINARY AIRCRAFT DESIGN

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DEDICATION

To the memory of my grandmother, Katheryn, I will never forget you

“The soul would have no rainbow had the eyes no tears”

and to my mother, Marleine

“This was better than basket weaving!”

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With any accomplishment in life, one often forgets the people that have helped pave the road, provided support or motivation, or helped pick you up when you were beaten down. I would like to thank my mother, Marleine, for all of her years of support (emotional and financial), encouragement, and love. Without you mom, I would have never achieved what I was capable of in life. You are my strength and anyone would be blessed to have you as a mother. Thank you poppa John for coming into my mother's and my life and providing her with love and me with the father I never had. I love you both with every bit of my being. You are the one constant in my life and the lights that you hold around my heart will never dim. You are the best friends that anyone could ever have.

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"To dream is freedom..."

"If one advances confidently in the direction of his dreams, and endeavours to live the life which he has imagined, he will meet with a success unexpected in common hours." –Thoreau

"Any path is only a path, and there is no affront, to oneself or to others, in dropping it if that is what your heart tells you... Look at every path closely and deliberately. Try it as many times as you think is necessary. Then ask yourself, and yourself alone, one question. Does this path have a heart? If it does, the path is good; if it doesn't it is of no use." –Carlos Casteneda

"Life's only limitations are those you set upon yourself, for as long as you strive hard enough anything is achievable."--Chad Williams

Thanks to all, Micha

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NOMENCLATURE

\$/RPM	Average Required Yield Per Revenue Passenger Mile
Acq\$	Acquisition price
ALCCA	Aircraft Life Cycle Cost Analysis
ANOVA	Analysis Of Variance
AR	Aspect Ratio
BL	Baseline
CC	Circulation Control
CCD	Central Composite Design
CDF	Cumulative Distribution Function
CLdes	Design lift coefficient
DM	Decision Matrix
DOC+I	Direct Operating Costs plus Interest
DoD	Department of Defense
DoE	Design of Experiments
EE	Economic Effectiveness parameter
EIS	Entry Into Service
EPNLdB	Estimated Perceived Noise Level in Decibels
FAA	Federal Aviation Administration
FAR	Federal Aviation Regulation
FLOPS	FLight OPTimization System
FON	Flyover Noise
FPI	Fast Probability Integration
FPR	Fan Pressure Ratio

FTK	Freight Tonne Kilometer
FY	Fiscal Year
HLFC	Hybrid Laminar Flow Control
HSCT	High Speed Civil Transport
IPPD	Integrated Product and Process Development
IPT	Integrated Product Team
LdgFL	Landing Field Length
LE	Leading Edge
M&S	Modeling and Simulation
MADM	Multi-Attribute Decision Making
MCDM	Multi-Criteria Decision Making
MCS	Monte Carlo Simulation
MDO	Multi-disciplinary Design Optimization
NASA	National Aeronautics and Space Administration
NCAT	National Center for Advanced Technologies
O&S	Operation and Support
OEC	Overall Evaluation Criteria
OPR	Overall Pressure Ratio
PDF	Probability Density Function
PE	Performance Effectiveness parameter
POS	Probability Of Success
QFD	Quality Function Deployment
R&D	Research and Development
RDS	Robust Design Simulation
RDT&E	Research, Development, Testing and Evaluation
ROI	Return on Investment
RPK	Revenue Passenger Kilometer
RSE	Response Surface Equation
RSM	Response Surface Methodology
SE	System Effectiveness parameter

SFC	Specific Fuel Consumption
SHref	Horizontal tail reference area
SLN	Sideline Noise
SVref	Vertical tail reference area
SW	Wing reference area
TAROC	Total Airplane Related Operating Costs
TCM	Technology Compatibility Matrix
TE	Trailing Edge
TIES	Technology Identification, Evaluation, and Selection
TIF	Technology Impact Forecasting
TIM	Technology Impact Matrix
TIT	Turbine Inlet Temperature
TOFL	Takeoff Field Length
TOGW	Takeoff Gross Weight
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TRL	Technology Readiness Level
TWR	Thrust to Weight Ratio
Vapp	Approach speed
VSLCDE	Virtual Stochastic Life Cycle Design Environment

SUMMARY

The changing global socio-economical and political environment is creating a paradigm shift in the aerospace industry. This paradigm shift calls for solutions that are beyond evolutionary databases and demands consideration of all aspects of the system's life cycle. The shift implies that a new means of evaluating the "goodness" of a system must be established and requires inclusion of three elements. The elements are as follows: consideration of the product life cycle in the early phases of design, new design methods to account for multiple criteria and uncertainty, and breakthrough technologies to meet aggressive performance and economic objectives of the future.

A new design method for complex systems was created as a response to the paradigm shift and was achieved with the use of statistical and probabilistic methods, including Response Surface Methods and Monte Carlo Simulations. The method accounts for the multi-criteria problem in the presence of design, operational, and technological uncertainty while allowing for the infusion and subsequent affordability assessment of immature technologies. The design method includes a forecasting environment whereby the decision-maker has the ability to easily assess and trade-off the impact of various technologies without sophisticated and time-consuming mathematical formulations. This objective was achieved by employing the use of Morphological analysis, forecasting analogies and techniques, and Multi-Attribute Decision Making techniques. Through the execution of the method, a family of design alternatives for a set

of customer requirements can be identified and assessed subjectively or objectively. This method allows for increased knowledge, reduced committed costs and increased design freedom leverage to produce high quality and competitive cost systems in a systematic and comprehensive manner and is called the Technology Identification, Evaluation, and Selection, or TIES, method.

The TIES method was demonstrated on a High Speed Civil Transport concept. This vehicle was chosen as a benchmark for the method due to the technically challenging customer requirements and the need for revolutionary advances over present day technological capabilities to obtain feasible configurations. The TIES method established the need and the product specifications and identified the most suitable set of technologies to satisfy all customer requirements in a probabilistic design setting.

CHAPTER I

MOTIVATION

In 1962, Thomas Kuhn wrote *The Structure of Scientific Revolutions* [1]. In this work, Kuhn argued that science does not progress in a steady, cumulative acquisition of knowledge “from lesser to greater truth, but remains fixated on a particular dogma or explanation – a paradigm.”[2] A paradigm is essentially a collection of beliefs, theories, standards, and methods shared by scientists that guide research efforts. Scientists accept this paradigm to be self-evident and “try to extend its scope by refining theories, explaining puzzling data, and establishing more precise measures of standards and phenomena.”[3] Based on this definition, traditional methods for aerospace systems design would be considered a paradigm, where the focus on maximizing performance while minimizing weight is the established paradigm. Historically in traditional design methods, the “principal elements were the iterative, sequential application of analyses based on the Newtonian principles of reductionism and mechanism; and syntheses utilizing the intuitive skills of a designer.”[4] This statement embodies the established paradigm in aerospace systems design.

Yet with any paradigm, a revolution eventually occurs. As Schombert noted, a crisis will occur that may expose the inadequacies of the current paradigm and may originate either exogenously or endogenously. When this occurs, the crisis “can only be resolved by an intellectual revolution that replaces the old paradigm with a new one.”[3] This phenomenon is called a *paradigm shift*. “A shift in the paradigm alters the fundamental concepts underlying research and inspires new standards of evidence, new research techniques, and new pathways of theory and experiment”[3] that are drastically different from the old tenets. One of the most notable paradigm shifts was from Ptolemaic cosmology, with the Earth at the center of the universe, which was overthrown after centuries of debate by Copernican heliocentrism, with the sun at the center of the Universe [1]. As with any revolution, there exists resistance to changing the way that things have always been. Ways of thinking will not change overnight, but will be transformed by constant evidence of the worth of the new way of thinking.

A paradigm shift has been occurring in the aerospace industry for the past two decades. The accepted paradigm is to design systems sequentially and iteratively to maximize performance based on minimum weight with cost and quality as a by-product. This school of thought is not sufficient for the rapidly changing global environment. In order to satisfy the demanding requirements of future systems, change is needed.

Changing Global Environment

The impetus for the paradigm shift in the aerospace industry is due to the changing global socio-economical and political environment. The shift is based on a multitude of contributing factors including the fervor for higher return on investment (ROI), reduced

spending budgets, increased system complexity, changing federal and environmental regulations, projected commercial traffic growth, and the desires of the travelling public for comfort, safety, and affordability [5]. Each factor has contributed to the need for a change in the manner in which aerospace systems are designed and the mentality in the approach to design. The *paradigm shift* is from “design for performance” to “design for affordability and quality”.

More for Less Mentality

Government and commercial industry retain the desire for systems or products with high quality, performance, and ROI, but with significantly lower and competitive costs. Here, ROI may be defined in either economic terms or in the ability of a system to perform a given mission. Making a profit is the focus of any commercial company. Yet, designing products at the outset with the end cost in mind has not been a priority. Cost considerations as a part of the design process is called *Design Justification*. Noble and Tanchoco state that “Design Justification is a term used to describe a design process where the economic ramifications of design decisions are considered concurrently with design development, and are used to guide the design process so as to result in the most economical criteria-satisfying design.”[6] Design Justification is in direct conflict with the traditional means of design for commercial aircraft and defense systems which has traditionally been performance driven and cost is not considered until the system is relatively mature [7]. Dillon observes that this design focus has resulted in systems that experience significant budget and schedule overruns [8]. Dean further notes that this trend has resulted in an exponential growth in production costs in fixed year dollars in the

last 60 years [9]. In particular, the first unit cost of large systems in the U.S. has been escalating at about 2.9% per year above inflation [10]. Increasing production costs translates directly into higher acquisition prices, ticket fares, and operating costs.

A simplified approach to increasing ROI is to maximize the difference between revenues and expenditures. However, commercial and defense procurement budgets are down more than 30% in the last 10 years, reducing the potential for increased revenues [11,12]. This is especially true for defense systems. Since the end of the Cold War in 1989, defense spending has been reduced drastically [11]. Therefore, in order to increase ROI, expenditures must be reduced. Note that in the context of this research, military ROI is analogous to weapons systems effectiveness described by Mavris [13]. Government and industry have taken an indirect and passive approach to increase ROI through reducing expenditures. Government has focused on down-sizing, reducing internal research and development (R&D) budgets by as much as 50% [12], and cancelling or reducing existing programs. Yet, “short production runs make it impossible to take advantage of the learning curve effects or to amortize initial investment costs.”[14] Industry has reduced expenditures through mergers or buyouts with competing companies, thereby reducing overhead and increasing market share. New or innovative programs that are not derivatives of existing systems have been dismissed to reduce economic risk, sunk costs, and potential loss of profitability. And reducing the R&D budgets or simply downsizing and laying off the workforce reduces expenditures.

On the commercial side, the Airline Deregulation Act of 1978 has drastically changed the commercial aviation sector in recent years. Sayles observes that deregulation “led to intense price competition, the entry of numerous low-cost (airlines), and the

development of hub-and-spokes networks...”[15] Although these aspects provide numerous benefits to the passenger, prosperity of the airlines has decreased due to increasing competition, increasing expenditures on aging aircraft, and escalating prices of new aircraft. Since 1978, the yield, or revenue per passenger mile (a measure of airline profit), has dropped from 12.27¢ to 7.48¢ in 1999, based on 1982 dollars [16]. To maintain market share, price competitions have led to slim profit margins. Low-cost airlines, such as AirTran and Vanguard, have exacerbated this with inexpensive fares resulting from extremely low indirect operating costs and market saturation. Finally, hub-and-spokes networks have drastically increased competition in many small and medium sized communities and created monopolistic behavior in the hubs. This increased competition has forced many airlines to reduce ticket fares, increase passenger amenities, and increase customer-oriented services in order to maintain or increase market share. Thus, the expenditures to attract or maintain a market have increased while revenue has remained constant or even been reduced. To complicate matters further, the expenditures are also increasing due to higher maintenance costs for an aging fleet and higher operating costs resulting from inefficient systems and technologies designed decades ago. At present, most airline companies are struggling to maintain slim profit margins resulting from increased competition. In fact, the U.S. Department of Transportation proposed new policies to remedy the fare wars within industry [17]. This approach would merely mask the problem of low ROI and high cost rather than directly deal with the issues of actively controlling expenditures.

Increasing Complexity

The skyrocketing production and acquisition costs are further compounded by the increasing complexity of the systems that are a consequence of higher performance expectations. This complexity increase results from the driving philosophy of “higher, faster, farther” which pervades the aerospace industry. To understand this concept, one must simply look at the evolution of modern aircraft from the Wright Flyer and the Fokker Eindecker to current systems such as the Boeing 777 or the F22 Raptor. Aircraft have evolved through many technological advances, both in product and process, to achieve the current performance characteristics [18]. For example, the skin of the body evolved from non-existent to fabric to aluminum and finally composite materials, fuel control from manual fuel-to-air mixing to Full Authority Digital Engine Control, and the list could go on. The complexities of the systems are continually increasing as the desire for higher, faster, and farther is pursued. Advancing performance from the state-of-the-art via increasing complexity is one source for the exponentially escalating costs as noted by Dean: *Cost is exponentially related to complexity* [9].

Environmental Regulations

Budget constraints and increased profits are not the only impetus for the rifts in the philosophy of aerospace systems design. An awareness of preserving the global environment is a growing factor. “Balancing the demands for industrial growth with the aspirations for sustaining and improving the quality of the environment is an [arduous] global challenge.”[19] Environmentally friendly systems are ones that comply with the regulations for reduced air emissions, reduced manifested hazardous waste, and reduced

noise levels imposed by national and international agencies. In general, increasing environmental compliance compromises the performance or cost of the system due to increased complexity. As a specific example, NASA investigated the feasibility of a second-generation supersonic transport, or a High Speed Civil Transport (HSCT), in the High Speed Research program in the 1990's. One of the primary obstacles to the success of an HSCT concept was compliance with the FAR Stage III Noise regulations. To meet this requirement, an excessively heavy mixer-ejector nozzle was suggested as a solution. Although the noise was reduced, the engine weight increased which increased the airframe weight, and degraded the system performance and lead to increased projected costs [20]. For future systems to comply with forthcoming or current regulations, technological advances in the state-of-the-art must be made. In general, *technological advances imply complexity, which implies increased costs.*

Traffic Growth and End-User Satisfaction

The projected commercial travel growth is also affecting the aerospace industry. Boeing predicted that in the next 20 years, world-wide economic growth will average 3.0% per year, passenger traffic growth will average 4.8% per year in revenue passenger kilometer (RPK), and cargo traffic growth will average 6.4% in freight tonne-kilometer (FTK) per year [21]. Airbus predicted that passenger traffic, in term of RPK, would increase at a rate of 4.98% per year from 1999 to 2018 and cargo growth at 5.9% FTK [22]. This potential growth in traffic is expected to strain the existing infrastructure, creating a need for considerable expansion of existing airports or construction of new ones [23]. Neither of these expensive and impractical alternatives will answer the

increased congestion problem. Thus, alternative approaches must be devised, such as the introduction of new or improved systems, increased throughput, or increased utilization. However, maximizing throughput and utilization of the existing carrier fleets will not be sufficient to meet future traffic demands. New systems are needed to offset the predicted growth. Boeing predicted that the market for new airplanes will double and be on the order of \$1.5 trillion over the next 20 years and that one-third of the current fleet will need to be replaced [21].

The desires of the travelling public are becoming increasingly important. The travelling public desires the timesaving associated with air travel but also demands high quality, efficiency, and safety at an affordable price. The Japanese automobile industry recognized the importance of designing quality into the products - "quality is the best way to assure long-term profitability." [24] The logic is simple: passengers are satisfied, hence more RPKs, hence more revenue and ROI for the airlines, hence more aircraft needed to meet the demand, then more orders for the manufacturers, more profit for the manufacturers, and so on. Improving quality and customer satisfaction is a winning situation for all parties involved.

The Need for Change: A Paradigm Shift

The factors contributing to the revolution in the existing paradigm of how aerospace systems are designed include the desire for reduced costs, increased profit, increased performance, increased environmental friendliness, and increased quality of the end product. The current NASA administration has noticed this shift in aviation focus and responded with the "Three Pillars for Success" program.

"To preserve our Nation's economic health and the welfare of the traveling public, NASA must provide high-risk technology advances for safer, cleaner, quieter, and more affordable air travel." [25]

-- Daniel S. Goldin, NASA Administrator

This quote is one pillar of NASA's "Three Pillars for Success" program. This program was designed to be a roadmap to focus U.S. aerospace endeavors for the next 20 years in accordance with the changing environment of future aviation. Another pillar is revolutionary technology leaps. "An enabling technology goal...is to provide next-generation design tools (and methods)...to increase design confidence and cut the development cycle time for aircraft in half." [25] Shorter design cycles invariably create cost reductions, put the product into production earlier, and respond to the customer or societal need quicker. Cycle time reduction also allows for faster insertion of current technology and mitigates the possibility that a technology will become obsolete while the product is in production.

Within the "Three Pillars for Success" program, long-term goals have been set for percent reductions in the factors contributing to the paradigm shift (affordability, safety, etc.) for next-generation vehicle concepts. For example, the affordability goal is to reduce the cost of air travel by 25% in the next 10 years and 50% in the next 25 years. To meet this challenge, technological breakthroughs need to be identified and developed to achieve the cost savings not possible through small, incremental improvements [26]. A technological breakthrough, as defined by Martino, is "an advance in the level of performance of some class of devices or techniques, perhaps based on previously unutilized principles, that significantly transcends the limits of prior devices or techniques," [27] while an evolutionary improvement is simply an incremental change in performance.

Dean and Unal also observed these factors and noted that “increasing performance and quality at lower costs implies that both government and industry must change the way they do business. Therefore, new philosophy (methods and techniques) and technology must be employed to design and produce high quality systems at low cost.”[28] This implies a new means of evaluating the “goodness” of an aircraft system must be established in lieu of the traditional minimization of gross weight or maximization of performance. Further, Mavris noted that aggressive future requirements call for solutions that are outside of evolutionary databases, while maintaining the importance of safe and affordable technology, and demand the consideration of all life cycle associated implications [29]. Three underlying themes are evident to meet the goals of the future and establish the new paradigm: life cycle considerations, technological breakthroughs, and new design methods.

The New Paradigm: Design for Affordability and Quality

A characteristic of any complex system is the multiplicity of the interactions within the system [30], such is the case with the new paradigm for aircraft or vehicle design. The goal of the new paradigm is to have the ability to design complex systems with high quality at a competitive cost to meet aggressive future customer requirements. To establish the new paradigm, an awareness of three elements is needed: life cycle considerations, breakthrough technologies, and new design methods. The elements are not independent but highly coupled.

Life Cycle Considerations

Why is consideration of the life cycle of a system important to a manufacturer? The life cycle phases of an aircraft include conceptual, preliminary, and detailed design, production, service, and retirement. The decisions made in the early phases have a considerable impact on the aircraft system in question. In particular, there is a strong “cost-knowledge-freedom” dependency from conceptual design to production, which can significantly influence the entire life cycle of a system, specifically cost and quality, or customer satisfaction. Mavris [29] adapted the idea of “cost-knowledge-freedom” to aircraft systems from Blanchard’s [31] generic notion of commitment of a product’s life cycle cost as shown in Figure 1. As the design progresses from conceptual design to product release in the traditional design approach, design freedom is lost almost immediately since a single configuration is often locked in as the foundation for all decisions. Design freedom is the ability to make engineering changes during the product development stages prior to product release. Small perturbations are performed on this configuration and any changes to the product specifications that occur in later phases, as the knowledge of the system increases, have significant cost implications.

The future design process, as discussed by Mavris [29], desires to shift these trends. The future design process focuses on the ability to carry along a family of design alternatives as facilitated through probabilistic design approaches. This “openness” of the design allows for more robust products that are less sensitive to changes in customer requirements as the product evolves. Consequently, costs are minimized when changes occur in the development cycle. Design freedom is further enhanced by increased knowledge about the product. To increase knowledge, non-traditional disciplines, such as

economics, reliability, supportability, etc., must be quantified concurrently with the product design in the early phases. Additionally, the use of higher fidelity, preliminary design and analysis tools in the early stages allows more knowledge to be brought forward. To accomplish this end, a modeling and simulation environment is needed to integrate the multiplicity of information, thus allowing rapid and cost-efficient product and process trade-offs. Hence, the keys to success of the new paradigm are making educated decisions (increasing knowledge) early on, and maintaining the ability to carry along a family of alternatives (design freedom leverage) without locking in costs [29].

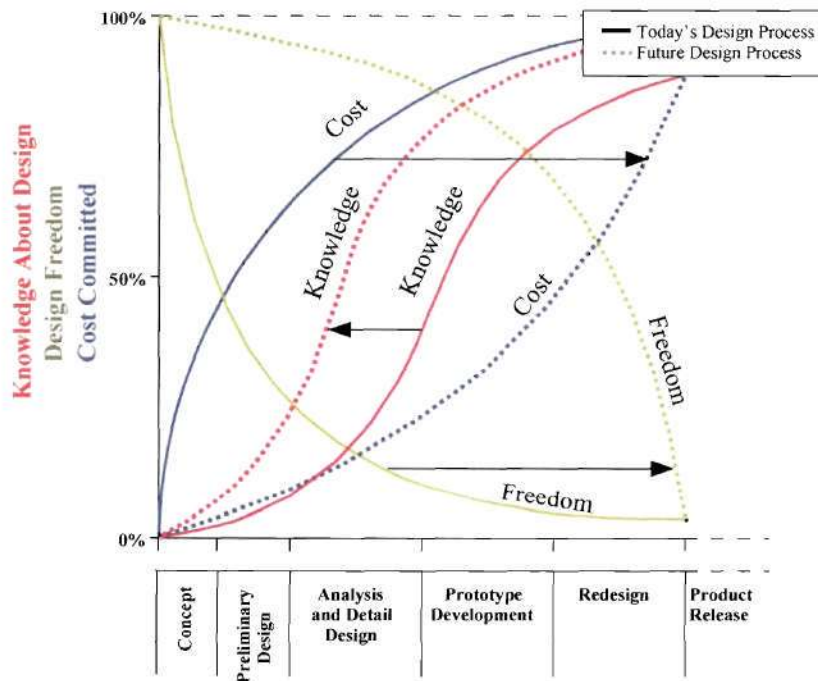


Figure 1: "Cost-Knowledge-Freedom" Shift for Future Design Methods [29]

In addition, when assessing the quality and robustness of a product, the complete life cycle of the product, not merely production and acquisition, must be considered. In order for quality to be achieved in a product, the design process must be customer focused. To do so, one must know who the customers are and what are their demands.

Taguchi recognized that “traditional engineering focused on solving problems, failure analysis, use of a repetitive process of design-build-test, testing one factor at a time, fire fighting, and studying in detail the problems associated with interactions of the factors involved. This approach costs more, takes more time, and isn't always successful.”[32] Taguchi combined engineering and statistical methods to achieve rapid improvements in costs and quality by optimizing product design and manufacturing processes so as to minimize rejection and rework, thus creating robust designs. His philosophy can be summarized with two simple statements [33]:

- 1) Quality should be measured by the deviation from a specified target value, rather than by conformance to pre-set tolerance limits.
- 2) Quality cannot be ensured through inspection and rework, but must be built in through the appropriate design of the process and product.

Finally, based on the concept of Design Justification, consideration of the cost ramifications of decisions in the conceptual and preliminary design stage will increase the potential for success of the system. Blanchard states, “it is imperative that future systems’ design and development efforts consider the overall effectiveness of a system as related to a specific consumer need and that these system requirements be viewed using a life cycle approach.”[31] From this discussion, a question immediately arises. *How does one increase design freedom and knowledge in the early phases of design to guarantee high quality, robust products that satisfy a set of potentially fluctuating customer requirements?*

Technological Breakthroughs

Why are breakthrough technologies needed? A recent National Research Council report urged that to achieve the goals set forth in the “Three Pillars for Success” program and to respond to the changing global environment, breakthrough technological capabilities, both evolutionary and revolutionary, are required [34]. However, manufacturers and operators are generally reluctant to adopt new technologies, beyond those that are incremental improvements or imposed by regulation. Ultimately, manufacturers and operators are driven by economic incentives, which implies that conventional or existing technologies are preferred in order to minimize investment costs and program risk [34].

Another problem, as stated by Bandte, is that off-the-shelf technologies are “readily available for implementation in the system, yet may be obsolete when the system is actually fielded.”[35] In general, commercial aerospace systems require 7 to 15 years from concept formulation until the product launch date [36]. Consequently, due to technology obsolescence, “a product using current technology to satisfy today’s customers may have little appeal when it appears for sale”[37] at the product launch date. In military systems, technology obsolescence is a major challenge due to the fact that the average acquisition time is 16 to 18 years [38]. Bandte further notes that “new technological solutions have to be found, applied to the components, and incorporated into the system.”[35] This must be considered in the beginning phases of design since the impact of adding technologies in the later phases will require a redesign of the existing system and significant cost implications as discussed previously. “But these technological solutions may only be at a conceptual stage in their development (and) several questions

remain concerning their readiness for implementation when needed and their actual performance level once implemented.”[35] Still, the technologies must be considered concurrently with the product design in the conceptual stage, even if they are not fully matured, so as to avoid obsolescence at product launch. Therefore, a need arises such that the impact of a technology on a system can be measured before the technology is fully matured and its complete ramifications known. A technology in a conceptual stage of development will be defined in this research as an *immature technology*, while a mature technology is one that has current full-scale commercial or military application.

Three issues arise from this discussion. First, significant technological breakthroughs are often required to meet future customer requirements. To avoid technology obsolescence at product launch, *the immature technologies should be developed concurrently with the initial concept feasibility studies*. Thus, the impact that a given immature technology may have on the system is *uncertain* and must be estimated. Second, a new technology must show the manufacturer or operator a high payoff with respect to performance, economics, and quality and at an acceptable risk. The high payoff technologies should then be provided sufficient resources and funding for further development. However, a quantifiable justification is required to optimally direct scarce R&D resources. Third, the design process takes a minimum of 7 years before service begins. Therefore, to include immature technologies in the conceptual phase and increase knowledge and take advantage of design freedom leverage, the decision-maker must have some means of predicting how the technologies will impact the system in the future, and what is required to mature the technologies. *This last issue requires that a technology forecast must be made.*

Technology forecasting is a prediction of the future characteristics (levels of performance such as speed or power) of useful machines, procedures, or techniques [27]. “Technology forecasting started in 1959 with Ralph Lenz’s Master’s thesis. Only in the late 1960’s did it get attention due to attempts to control the mushrooming growth and planning in R&D.”[39] Forecasting reduces uncertainty about the future but does not eliminate it completely. Forecasting provides a better quantitative view of the future and the evolutionary path to be followed so as to lead to more informed decisions. Forecasting also provides a quantitative means of estimating the risks associated with a project [37].

If immature technologies are to be considered in the conceptual and preliminary phases of design, additional questions arise:

How does one identify which technologies should be considered in response to a set of customer requirements?

How does one determine the maturity of a technology?

How does one model and assess the impact of an immature technology in the early phases of design if a mathematical formulation does not exist, and what are the consequences to the design in terms of performance, cost, schedule, and risk?

How much investment monies are needed to acquire a given level of performance in a given time frame?

How does one select the technologies that have the most significant system impact and should be considered for further development funding?

New Design Methods

What are the fundamental reasons for new design methods? The answer is three-fold. Modern design is probabilistic in nature due to inherent uncertainty associated with the design. Multiple criteria exist rather than the traditional single objective of maximum performance. And, rapid assessments are needed to reduce cycle time.

Uncertainty can be defined as a lack of complete knowledge, or a difference between reality and what is expected. If one considers the system from a life cycle perspective, the lack of knowledge arises from ambiguous customer requirements, analysis tool fidelity, manufacturing tolerances, technological uncertainty levels, and uncontrollable factors such as daily fuel costs [40,41]. Traditionally, uncertainty in structural loads, mathematical models, economic assumptions, potential technological risks, etc., has been represented deterministically using factors of safety and exaggerated assumptions about reality [42]. This is an unsophisticated means of handling uncertainty. A more appropriate method is to incorporate mathematical models of probability and statistics to account for uncertainty in a more rigorous fashion, especially if knowledge of later design phases is to be brought earlier in the process. Hence, the traditional point estimates or assumptions made throughout the design must be replaced by probabilistic estimates that quantify the uncertainty of the predicted outcome [43,44]. Many fields have taken this approach including structural design, economic theory, and meteorology [45]. Based on this rationale, the evolving modern aircraft design process *must be* a probabilistic rather than a traditional deterministic approach and, therefore will require a new toolbox of design methods.

Another reason for new design methods is that the traditional, one-dimensional design objective of maximum performance is no longer valid. The objective is now multi-dimensional based on the number of customers and their multiple requirements to be satisfied. As with any complex system, no single, exclusive customer requirement or overall objective exists. For aircraft systems, the customers include all parties inherently associated with the design, operation, use, and regulation of the aircraft, including airframe and engine manufacturers, regulatory entities, airlines, airports, and passengers. Consequently, new methods for evaluating designs are needed that can capture the multiple, often conflicting, objectives (or criteria) to identify design alternatives that may “best” satisfy all customers.

Although the concept of multi-criteria evaluation and selection is relatively new in the field of aerospace engineering, Hwang notes that the study of multiple criteria has existed for over forty years in economics, marketing research, psychometrics, and many other fields [46]. In the context of decision-making, Bandte points out that “criteria are customer supplied guidelines that form the bases for the decision-making process. These criteria play the essential role in the decision making process, deeming an alternative solution successful when customer desires are met. If the decision problem entails several criteria, experience has shown that not all are of equal importance to the customer. Which criteria is more important...is often not for the designer to decide, but must be [captured within] the decision-making process.”[35] The balancing of these criteria is paramount to the success of the design since the outcome depends heavily on the preference ordering (or customer subjectivity) of the criteria and may produce drastically different design solutions depending on which criterion is considered more important [35].

The final motivation for a set of new design methods is that a modeling and simulation environment is needed to model concept alternatives in the conceptual stages of design and rapidly determine the implications to the customer requirements. These trade-offs are currently performed in monolithic or legacy vehicle sizing and synthesis codes. A vehicle sizing and synthesis code is a multi-disciplinary tool (e.g., aerodynamics, structures, mission analysis) that calculates in an iterative fashion a vehicle weight and performance based on a specific mission. This environment must be expanded to capture the non-traditional disciplines, such as economics, to incorporate and quantitatively estimate the impact of immature technologies in addition to the traditional functions.

If new design methods are a required element of the new paradigm, the following questions arise:

What are the current probabilistic techniques to capture the uncertainty?

Which technique is more appropriate for a given stage of the design process?

What are the different multiple criteria selection techniques?

How does one capture the subjectivity of multiple and conflicting customer requirements?

How does one create a modeling and simulation environment to facilitate quantitative evaluations to substantiate decisions in the early stages of design?

Drawing on the discussion of the three elements needed to establish the new paradigm, a generalized goal may be stated. The ultimate goal of this dissertation is to create a comprehensive and structured method whereby complex systems can be designed with high quality at a competitive cost to meet future customer requirements. The method must have a balance of life cycle considerations, new design methods, and a means to infuse breakthrough technologies as shown in Figure 2. The goal of this research is to address many of these issues with particular emphasis on new technologies and decision-making techniques as will be discussed and outlined in Chapter II.

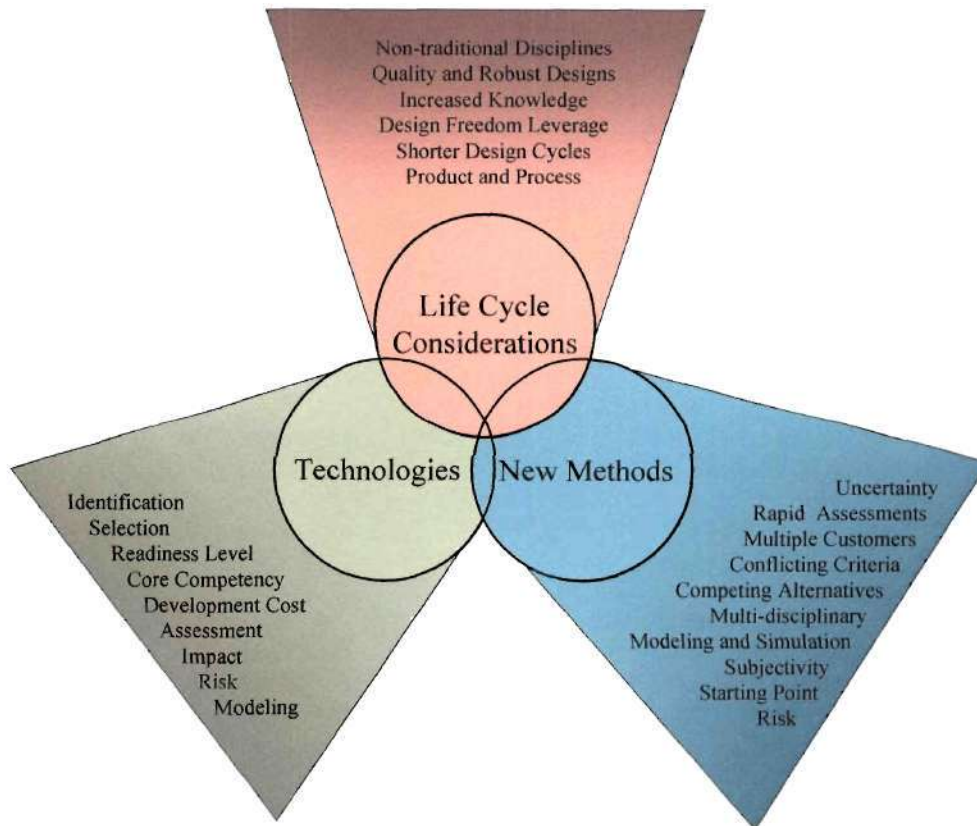


Figure 2: Elements of the New Paradigm

CHAPTER II

BACKGROUND

Prior to the identification of specific research questions to be addressed, the current state-of-the-art frameworks and approaches to the new paradigm are reviewed to determine what deficiencies exist for the three paradigm elements. Also of relevance, the identification of various techniques and methods that could be used for the new paradigm elements, such as probabilistic techniques to capture and quantify design uncertainty, product selection techniques for multiple customer criteria, and traditional resource allocation approaches. Finally, the importance of a modeling and simulation environment is discussed.

Design Frameworks and Approaches

Integrated Product and Process Development

In 1993, the National Center for Advanced Technologies (NCAT) formed the Multi-Association Industry Affordability Task Force Executive Committee to develop the strategies and actions necessary for government and industry to meet the challenges of future defense and commercial systems [47]. A primary finding of the committee was the

identification of the Integrated Product and Process Development (IPPD) method as a key enabler to obtain producible and affordable products. The committee defined IPPD as a “management methodology [or strategy] that incorporates a systematic approach to the early integration and concurrent application of all the disciplines that play a part throughout the system’s life cycle.”[48]

The Department of Defense recognized the merit of IPPD with regards to the Defense Acquisition Program and refined the original NCAT committee definition. “IPPD is a management technique that integrates all acquisition activities starting with requirements definition through production, fielding/deployment and operational support in order to optimize the design, manufacturing, business, and supportability processes. At the core of IPPD implementation are Integrated Product Teams (IPTs).”[49] “IPPD has its roots in integrated design and production practices, Concurrent Engineering, and Total Quality Management. In the early 1980s, U.S. industry used the concept of integrated design as a way to improve global competitiveness.”[50] For completeness, Concurrent Engineering is a systematic approach to the integrated, concurrent design of products and their related processes, including manufacture and support. This approach is intended to cause the developers, from the outset, to consider all elements of the product life cycle from conception through disposal, including quality, cost, schedule, and user requirements [51].

At the heart of the IPPD concept is the focus on the customer and meeting the customer needs. Although no single implementation strategy exists for IPPD, the generic IPPD process is a disciplined, systems engineering approach that entails an iterative scheme between customer requirements, products, and associated processes. In the Department of Defense's "Guide to IPPD", key tenets were identified to effectively implement IPPD and include: customer focus, concurrent development of products and processes, multidisciplinary teamwork, robust design and improved process quality, and proactive identification and management of risk [50]. From a top level, both IPPD and Concurrent Engineering respond to life cycle considerations along with identifying the multiplicity of customer requirements.

The payoffs of applying IPPD principles to the design of a product are reduced cost, reduced development time, and reduced risk while simultaneously increasing quality. These payoffs are achieved due to the integration of design, manufacturing, business, and supportability considerations in the early phases of the design process, thus reducing costly design changes in later phases as shown in Figure 3. "In a traditional approach, the largest number of (design) changes occur late in development, when change costs are high, resulting in higher program costs. In an IPPD process, the bulk of changes occur early in the development (due to consideration of the entire life cycle of the product), when change costs are low, resulting in lower program costs." [50] This notion is analogous to Mavris' sentiments of "cost-knowledge-freedom".

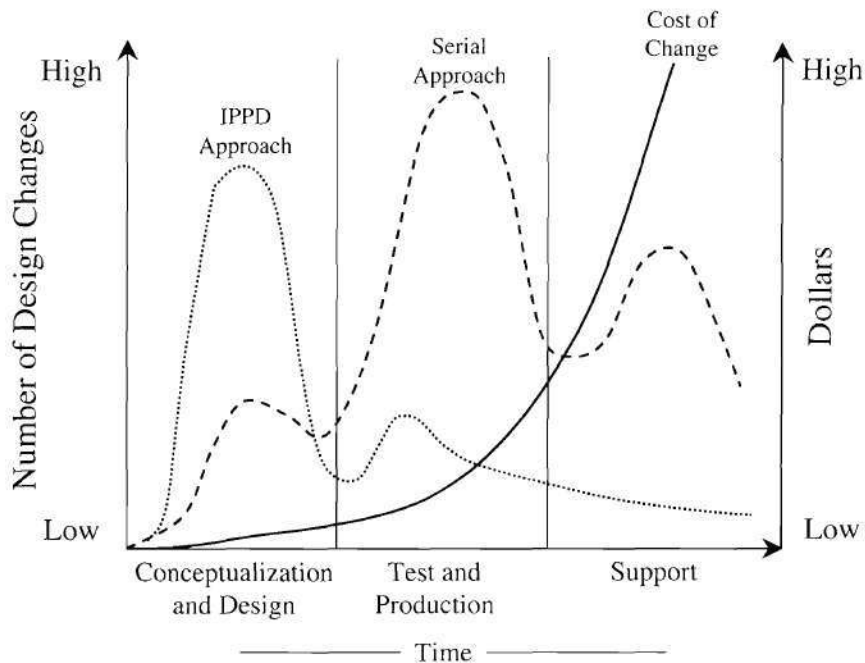


Figure 3: Serial versus IPPD Approach to Design [50]

Unfortunately, the primary item lacking in the NCAT and DoD vision of IPPD is a structured guideline on *how* to implement IPPD. What are the steps to follow? What are the techniques and tools needed for each step? How are the results evaluated? What are the options? Where does the process start? Schrage recommended that to obtain affordable systems within an IPPD approach, simultaneous product and process trade-offs must be performed throughout the design process as illustrated in Figure 4 [48]. Starting from conceptual design, the clockwise flow on the outer ring represents the traditional, serial design approach. Schrage observes that the “functional decomposition allows system design trades during conceptual design, component trades during preliminary design, and part design during detailed design. Unfortunately, this is approached as an open loop system, and, when the usual manufacturing process incompatibilities are encountered, the only solution is to make design changes and apply

recomposition activities around the left hand outer loop.”[48] IPPD is needed as the core strategy necessary to break the inefficiencies of traditional methods and create an environment whereby concurrent product and process trades may be performed at the system, component, and part levels.

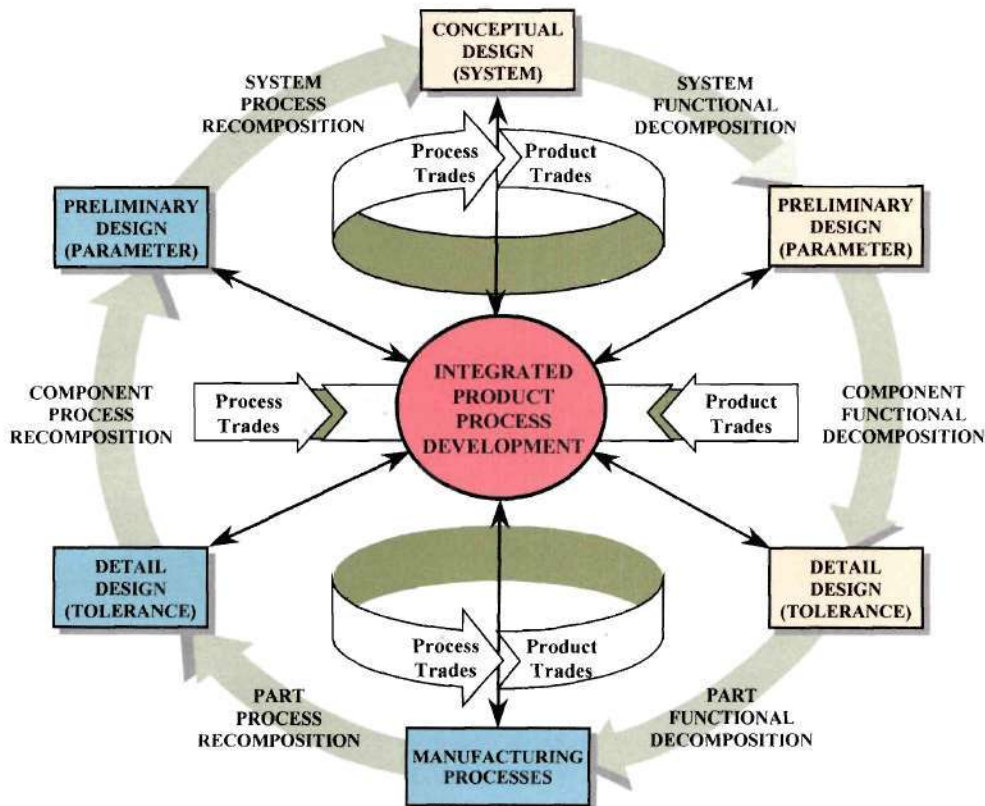


Figure 4: Integrated Product and Process Development Framework [48]

To implement the IPPD strategy, Schrage proposed four elements to guide the development of a product within the IPPD framework as evolved out of Concurrent Engineering principles [52]. The elements are quality engineering methods, systems engineering methods, a computer integrated environment, and top-down design decision support processes as shown in Figure 5.

At the core of the approach is a top-down design decision support process.

“Decision support is an essential element that can support a trade-off process and can be used to focus efforts on design goals. It supplies a logical, rational means for including factors that must be considered when making a decision.”[53] Systems engineering methods are product driven and decomposition-oriented, while quality engineering methods are statistically based, process driven and recomposition-oriented. Finally, a “computer-integrated environment is needed to facilitate the process, reduce the design cycle time, and provide a transparent and seamless integration.”[29]

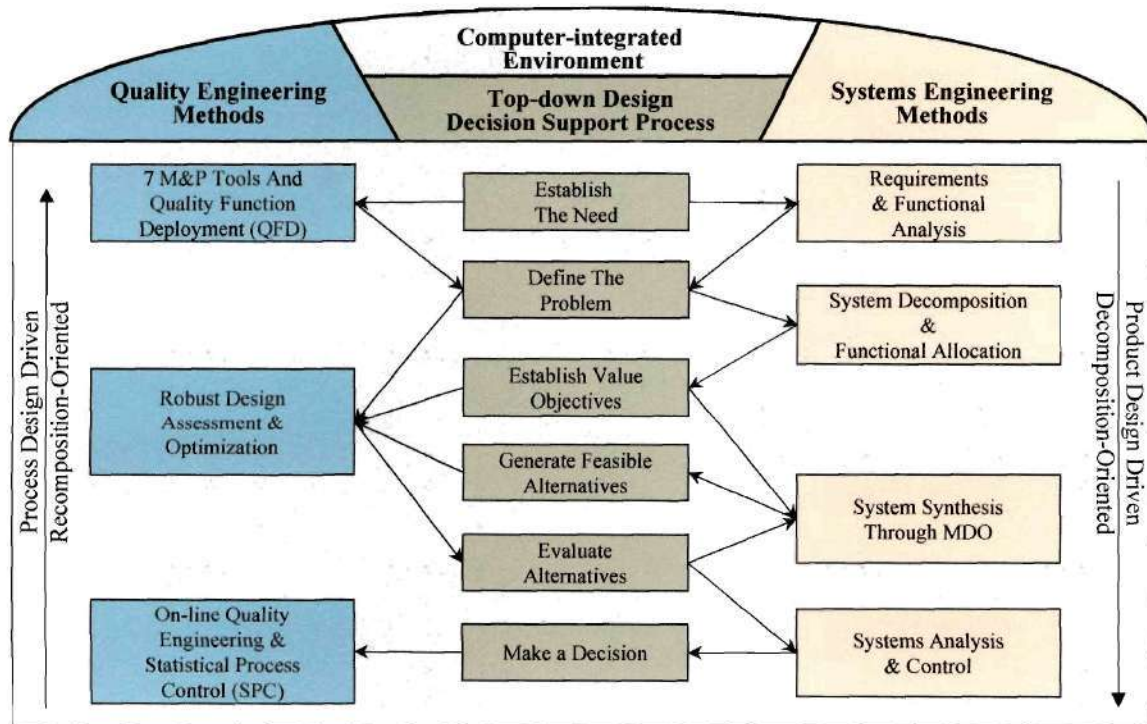


Figure 5: IPPD implementation [52]

The steps to execute Schrage's proposed approach begin with "Establishing the Need" and conclude with "Make a Decision". The techniques and methods required to execute each step are listed under the quality and systems engineering methods. The arrows into the top-down design decision support are the heart of the trade-off assessments and information flow to accomplish each step. For example, the importance of the "Robust Design Assessment and Optimization" is evident by the number of arrows entering and exiting the box. The primary design iteration loop in the IPPD approach consists of generating feasible alternatives, performing a robust design assessment, evaluating the alternatives, and then applying Multidisciplinary Design Optimization (MDO) techniques to identify the most robust design alternative. Robust design is defined as the "systematic approach to finding optimum values of design factors, which result in economical designs with low variability." [24] Schrage's approach has been applied to numerous vehicle concepts in the graduate course "Introduction to Concurrent Engineering" in the School of Aerospace Engineering at the Georgia Institute of Technology [52]. This approach is similar to the one proposed by Prasad [54]. The main ingredients missing are the explicit ability to quantify the impact of technologies and the balancing of multiple customer requirements.

Another method was proposed by James Gregory and Associates and is called *IPPD for Science & Technology*. "This method was originally developed for the U.S. Air Force in conjunction with approximately 30 other companies in the defense and aerospace industry. The basic principle of the method is to achieve the best value of a concept by balancing cost, performance, producibility, supportability, schedule, and risk." [11] This approach provided a very amenable graphical interface for the user to follow through the

steps proposed by Schrage. Yet, no specific means of the issues associated with the infusion of new technologies are captured in the framework, nor how to generate the information required to make informed decisions.

Robust Design Simulation

Robust Design Simulation (RDS) is a design method that evolved out of the IPPD approach. RDS is a probabilistic, multidisciplinary approach to aircraft design for which customer satisfaction is the ultimate design objective, as shown in Figure 6 [55]. RDS concurrently considers product and process characteristics subject to anticipated technology infusion, economic and discipline uncertainties, and technological and schedule risk so as to yield robust design solutions that maximize customer satisfaction subject to design and environmental constraints [56].

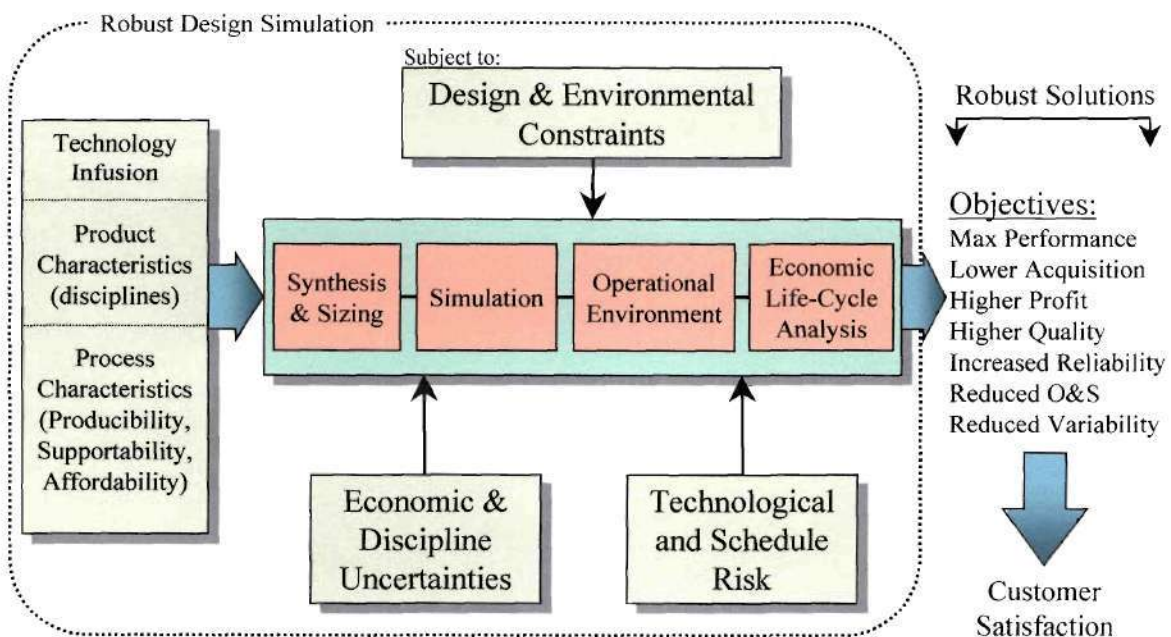


Figure 6: Robust Design Simulation Method [55]

Industry has attempted to incorporate robust methods through the use of Statistical Process Control or Six Sigma approaches. Yet, these approaches address manufacturing variability only in the later design stages. RDS attempts to bring the later issues of the design process forward, as is the case with IPPD. However, RDS is merely a conceptual method. Mavris proposed a four-step approach to implement RDS. For a given aircraft and a set of customer requirements, the steps are as follows [57]:

- 1) *Screening Test*: system level screening test of pertinent design and economic variables via a linear sensitivity investigation
- 2) *Create Response Surface Equations*: important variables from step 1 are used to define the customer requirements as a function of those variables through the use of Design of Experiments
- 3) *Introduce Uncertainty*: introduce uncertainty to economic variables and create another set of equations that represent the customer requirements as a function of design variables subject to economic uncertainty, given in terms of confidence levels
- 4) *Obtain Robust Solution*: determine the solutions that maximize the probability of achieving values below the target customer requirements

The primary application for the RDS method was a notional High Speed Civil Transport [55,56,57]. In each application, the focus was a proof of concept of applying Response Surface Methods and the introduction, and subsequent influence, of economic uncertainty on the affordability of the system. The investigations matured the use of probabilistic methods and the inclusion of affordability evaluations concurrently with design evaluations. However, as was the case with the IPPD approach, no specific means of evaluating or infusing new technologies was captured. Further, a single objective

function, not a multi-criteria objective, was used to determine the optimal, robust solution. The RDS method also locked the approach into a single class of vehicles to respond to a set of customer requirements. The method was applied after the initial stages of design had commenced, that is, the method began with a baseline configuration and did not have a means to generate a starting point, unlike IPPD which generates a concept with quality engineering methods such as the Quality Function Deployment technique.

Concept Feasibility and Viability Method

Another method was developed by Mavris [41,58] and Kirby [59] to address the inclusion of technologies within the design process and evolved from the RDS method as depicted in Figure 7. The five-step method takes a systems approach to assessing design alternatives. The method begins with a problem definition to identify the customer requirements (customer focus), uncertainty models (probabilistic design), and analysis tools (modeling and simulation environment). Next, the system feasibility is evaluated via probabilistic design techniques. If the system feasibility is unacceptable to the decision-maker, new technologies are infused. Finally, a decision is made. This method was applied to three commercial transports: a high capacity, long range transport [41], a supersonic transport [58], and a medium range intra-continental transport [59]. In each of the three investigations, the customer requirements were defined and a design space was investigated for system feasibility. None of the vehicle concepts could meet the defined customer requirements with present day technologies. Thus, new technologies were needed, as shown by Step 4.

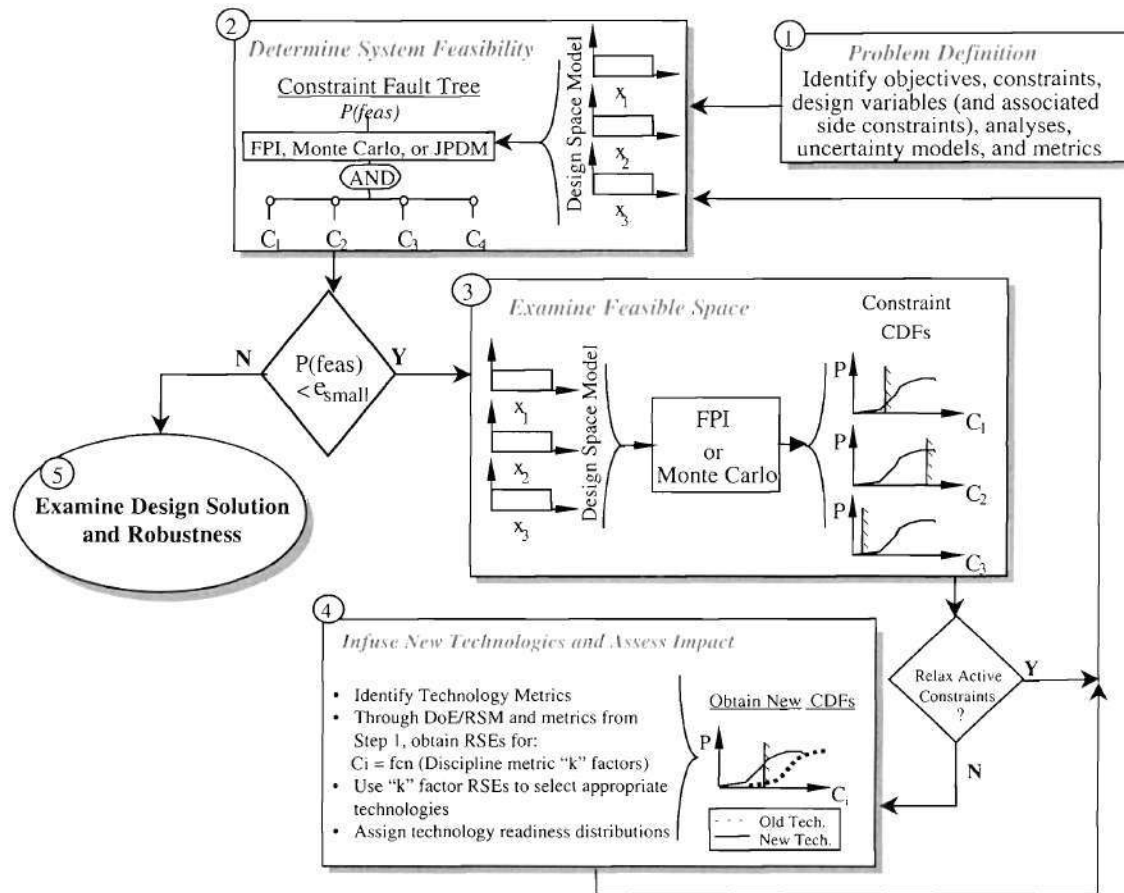


Figure 7: Concept Feasibility and Viability Method [41,58,59]

However, the approach taken for infusing technologies was a random selection of potential technology candidates. There were no guidelines as to which technologies to infuse to the system, nor which technology mixes were superior, resulting in a simplified analysis. Also, the subjectivity and balancing of the multiple customer requirements were not addressed and the method was applied after the initial stages of design had commenced, as was the case with the RDS method.

One of the issues this approach did address was how to represent the impact of technological uncertainty in a modeling and simulation environment. Each of the investigations addressed this issue through the use of disciplinary metric "k" factors. The

“k” factors modified technical metrics, such as specific fuel consumption, lift-to-drag ratio, and component weights, which resulted from an analysis or sizing tool. The modification was essentially a change in the technical metric, either enhancement or degradation. In effect, the “k” factors simulated the discontinuity in benefits or penalties associated with the addition of a new technology. Each technology was modeled as a vector of “k” factors which included multiple elements of benefits and penalties to the system. This was an appropriate approach when no mathematical formulation existed about an immature technology and was similar to Boeing’s investigation of the potential of laminar flow technologies applied to a supersonic transport [60]. Although Boeing performed extensive detailed studies on the impact of laminar flow, once the technology was integrated into the system, the technology was modeled as deltas, or “k” factors to the different disciplinary metrics. Finally, the uncertainty associated with immaturity was assumed to be normally distributed around a given impact, or “k” factor, but with no justification of the assumed shape or how the shape would change as the technology matured.

The concept feasibility and viability method in Figure 7 addressed technology modeling in the conceptual phases of design along with probabilistic design techniques. However, the method did not address the conflicting customer requirements, identification of technologies, technology immaturity modeling justification, starting point of the analysis, and the final product selection.

DANTE Model

The Dynamic Appraisal of Network Technologies and Equipment (DANTE) model was developed around 1980 to address the formulation and evaluation of advanced manufacturing technology programs. The DANTE model contains seven steps for selecting and evaluating new technology investment programs. As described by Danila, the steps are as follows [61]:

- 1) *Identification*: problem context, objectives, technologies and resources needed using checklists, brainstorming, and Delphi techniques
- 2) *Configurations*: construct all possible configurations of technology investment programs using support graph theory and Delphi techniques
- 3) *Dichotomy of criteria*: categorize all evaluation criteria as quantitative or qualitative
- 4) *Evaluation*: calculate all quantitative and appraise all qualitative criteria
- 5) *Aggregation*: rank the different alternatives based on different subjective weighting scenarios with multi-attribute decision making techniques
- 6) *Negotiation*: examine the feasibility of the technology programs with respect to the criteria and resources available
- 7) *Action*: select a solution and action plan that will ensure the realization of all benefits from the selected alternatives

As is evident, the DANTE model follows the same structure as Schrage's IPPD and the concept feasibility and viability method of defining the problem, evaluating the alternatives, and making a decision. Yet, the DANTE model incorporates technologies and available resources at the outset of the process and addresses the issue of multiple criteria in the Aggregation step. However, the technologies and the criteria were assessed

deterministically and the method relies heavily on intuitive tools, rather than analytical, to quantify the alternatives. This approach is difficult to justify the allocation of scarce resources due to the lack of quantitative analysis results. However, the general DANTE model framework is a worthwhile approach in that it addresses elements of the breakthrough technologies in addition to the subjectivity of multiple criteria.

Virtual Stochastic Life-Cycle Design Environment

The Virtual Stochastic Life-Cycle Design Environment (VSLCDE) was proposed by Mavris as an all-encompassing framework to address the issues of the previously discussed methods and result in affordable systems. Affordability, in this context, is defined as the ratio of the system effectiveness (or benefit supplied to the system) to the cost to achieve that effectiveness. An adaptation of the general framework originally proposed is shown in Figure 8 [29]. The focus of the VSLCDE is to “facilitate design decision-making over time (at any level of the organization) in the presence of uncertainty, allowing for affordable solutions to be reached with adequate confidence.”[62] In fact, VSLCDE is a compilation of Schrage’s IPPD approach, the RDS approach, and the concept feasibility and viability method. However, VSLCDE was proposed as a framework but provided no structured means for implementation and the shortcomings of the contributing methods still exists. The elements for the paradigm exist within the VSLCDE framework, but in no cohesive manner for applications.

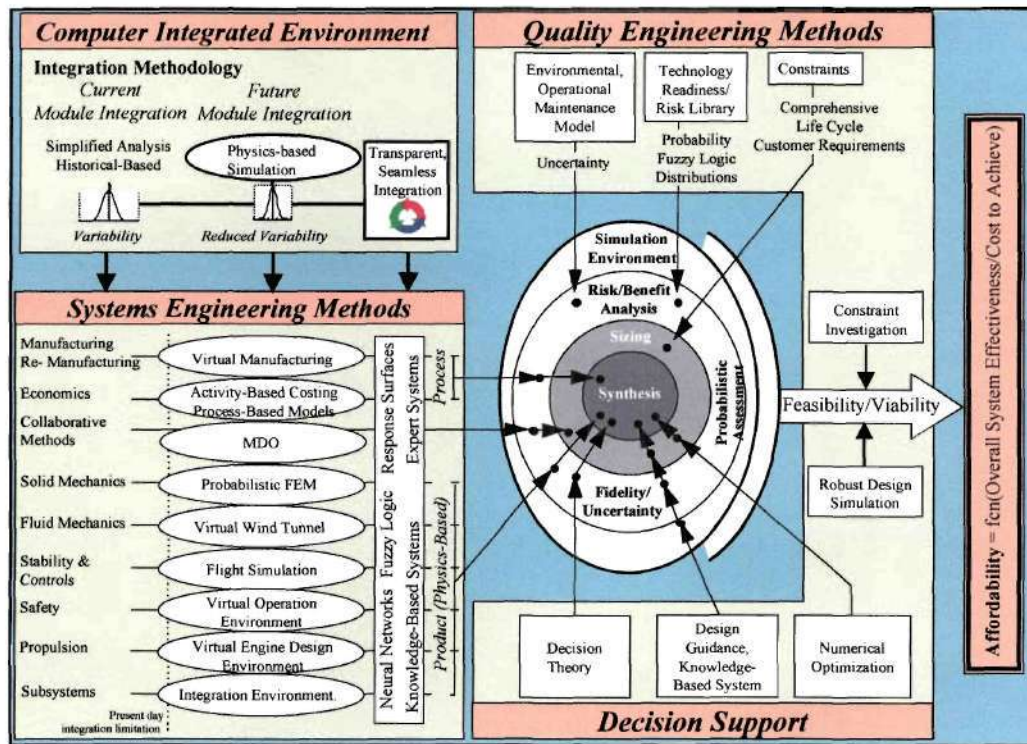


Figure 8: Virtual Stochastic Life-Cycle Design Environment [29]

Summary of Design Frameworks and Approaches

The five design approaches discussed contain pieces needed for the new paradigm. The IPPD approach addresses the life cycle considerations of a product. The RDS method addresses probabilistic techniques and robust solutions. The concept feasibility and viability method addresses new methods with probabilistic design techniques and technology modeling. The DANTE model addresses breakthrough technologies with the identification and evaluation of technologies, available resources, and multiple criteria. And finally, the VSLCDE qualitatively discusses the elements, but provides only piecewise structure for implementation. None of the approaches in isolation can respond to all three paradigm elements concurrently. Thus, drawing on the most relevant aspects of the five approaches, a generic design framework can be established as:

- *Define the problem*
- *Define vehicle and technology concepts*
- *Investigate the design space via a modeling and simulation environment*
- *Determine system feasibility*
- *Identify technology alternatives based on needed improvements*
- *Evaluate technology alternatives via a modeling and simulation environment*
- *Select the best family of alternatives responding to the customer needs*

Enabling Techniques

To respond to the generic framework for the new paradigm, enabling techniques from technical, operational, and mathematical fields must be identified so as to determine possible solutions to the shortcomings of the design frameworks and approaches presented. The techniques include probabilistic design methods to address uncertainty and efficient means of design alternative evaluations, multiple criteria selection techniques, traditional resource allocation approaches to new technology developments, and the need for a modeling and simulation environment.

Probabilistic Design Methods

The design of complex systems is immersed in uncertainty due to incomplete knowledge about the system and the behavior of the system in a relevant environment. As stated previously, the new paradigm design methods must be probabilistic. Traditional methods of design space exploration were based on the designer's intuitive knowledge of what the responding system might look like. A designer would perform paper study trades, and then build, test, fly, and modify the system as needed. More recent methods have established a starting point as before, defined a design space, and then applied

optimization schemes (e.g., gradient based, method of feasible directions [63]) to a computer simulation or sizing code to get to the “best” configuration. This approach is indicative of recent Multi-disciplinary Design Optimization (MDO) initiatives [64]. Although advanced from traditional techniques, MDO techniques do not explicitly consider the uncertainty associated with the design process or robustness, nor do they include life cycle considerations, only the traditional disciplines. MDO is very inefficient due to the number of function calls required with minimal information regarding the entire design space.

An alternative approach is needed that must be probabilistic in nature. Mavris observed that the “multi-disciplinary, life-cycle nature of the [design] problem introduces uncertainty associated with imprecise knowledge in the early phases (ambiguity, design uncertainty), analytical tool fidelity, operational environment, and...new technologies. Uncertainty may be modeled and its effects quantified through the use of....probabilistic techniques.”[29] The SAE Standard AIR5086 provides a description of recent perceptions and limitations of current probabilistic techniques [65]. “One of the major obstacles in applying probabilistic design methods is accommodating the large variety of existing deterministic computer codes.”[43] Rather than modifying the existing deterministic design tools, a more generic approach would be to have a “wrapper” that is linked to the original tool and controls the probabilistic assessment [43].

A Monte Carlo Simulation is the most accurate probabilistic technique to simulate reality, or uncertainty, by randomly generating values within a pre-specified range. Typically, the precision is proportional to the square root of the number of random cases used [66]. By assigning probability estimates to the design, operational, or technological

input parameters of an analysis code (within a range of interest), a probabilistic approach guarantees that all values are kept as possible solutions [67]. Fox and Mavris suggest three efficient probabilistic methods by which this space can be investigated for feasible solutions [68,69]:

- 1) Linkage of an analysis code with a Monte Carlo Simulation
- 2) Linkage of a metamodel of an analysis code with a Monte Carlo Simulation
- 3) Approximate the Monte Carlo with a Fast Probability Integration technique

The end result of each method is a cumulative distribution function (CDF) for each of the desired objectives or metrics as seen in Figure 9. The CDF represents how the metric behaves as a result of all the possible design variable combinations and in essence, defines and bounds the space of interest, whether the space be design, technological, or economical. At a probability level of 0% ($P=0\%$), the metric value is the best that can ever be achieved with the defined space, assuming that the CDFs probability levels (or P-levels) are increasing with increasing metric values. At $P=100\%$, the entire space falls below the corresponding metric value. Two statistical techniques that enable a probabilistic design approach include the Response Surface Methodology to create a metamodel of the customer requirements and the Fast Probability Integration technique. The theory behind each approach is briefly discussed herein.

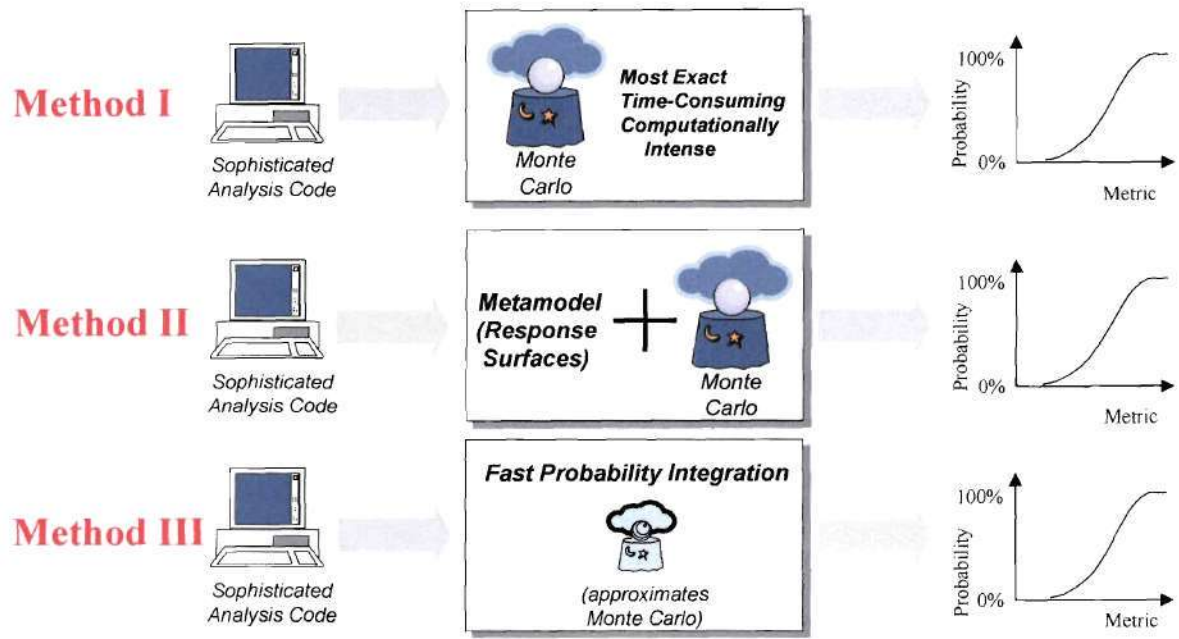


Figure 9: Probabilistic Design Methods

Response Surface Methodology Background

“Response Surface Methodology (RSM) comprises a group of statistical techniques for empirical model building and model exploitation. By careful design and analysis of experiments, it seeks to relate a response, or output variable to the levels of a number of predictors, or input variables, that affect it.” [70]

RSM has been a successful technique for efficiently building and optimizing empirical models of continuous functions since the 1950’s in chemical and mechanical engineering, chemistry, agriculture, [45] and more recently in aerospace systems design [55,71]. The use of RSM provides significant insight to a previously unknown or complicated response behavior in an efficient manner. RSM approximates the underlying dependence of output metrics to input parameters, over a limited region of input variable ranges, with an empirical polynomial relationship based on a given set of data. The variable ranges for which the region is defined are established via IPTs or brainstorming

activities and may be limited by code fidelity or to the limited extent that a polynomial may approximate a behavior. In most practical applications, the relationship is quadratic and can be represented as a Taylor series approximation [45,70] in the form in Equation 1, although other relationships may be employed. Typically, the method of least squares is used to estimate the coefficients. The resulting relationship is called a Response Surface Equation (RSE). Once Equation 1 is determined based on 'n' input variables, it can be used in lieu of more sophisticated, time-consuming analysis codes to predict and optimize the response of a sub-system or an entire system if the error of approximation, ϵ , is small. Subsequently, the RSE can be directly linked to a Monte Carlo Simulation to perform the probabilistic assessment.

$$R = b_o + \sum_{i=1}^n b_i x_i + \sum_{i=1}^n b_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^n b_{ij} x_i x_j + \epsilon \quad (1)$$

where:	R	response of interest
	b_o	intercept term
	b_i	regressed coefficient for 1 st order terms
	b_{ii}	regressed coefficient for 2 nd order terms
	b_{ij}	regressed coefficient for cross-product terms
	x_i	main effect of independent variables
	x_i^2	quadratic effect of independent variables
	$x_i x_j$	2 nd order interaction of independent variables
	ϵ	error associated with 2 nd order approximation

The efficiency of an RSM approach to building the model in Equation 1 lies in the minimal amount of data required to establish the functional relationship. Unlike classical one-variable-at-a-time strategies, the RSM approach, through careful selection of how the data is generated, is inexpensive and less computationally intense. The data needed for

the RSM is generated via an experimental design or Design of Experiments (DoE) technique. Montgomery defines an experimental design as a “test or series of tests in which *purposeful* changes are made to the input variables of a process or system so that we may observe and identify the reasons for change in the output response.”[72] In the context of this research, the “tests” are computer code simulations to generate the data required for the model building. Dean points out that a “DoE is the application of geometric principles to statistical sampling to obtain desired results such as minimizing the number of experiments [or computer simulations] necessary to obtain the answer to a problem or minimizing the variance of estimated coefficients obtained through regression.”[73] For a second order model, as in Equation 1, the experimental design must have at least three levels (or values) for each independent variable and numerous classes of designs may be used [72].

Four experimental design classes are listed in Table I in addition to the number of simulations required to build the model. Evaluation of all possible combinations of the input variables at three levels leads to an excessively high number of cases to be tested. In fact, if twelve variables are to be tested at three levels (two extremes and a midpoint value to account for non-linear effects), 531,441 cases are required. This is known as a full factorial design. Various geometric techniques including Box-Behnken Designs, Central Composite Designs (CCD), and D-Optimal Designs have been created to reduce the number of data points, or required simulations, to a more reasonable number to generate the model. References [45,70,72] provide detailed information regarding these designs and how they are created. The type of design chosen to build a model is based on the efficiency of the computer simulations. Bandte points out that the face-centered CCD

is very efficient for most model building. An example face-centered CCD for three variables (X_1, X_2, X_3) is listed in Table II, where the "-1", "0", and "+1" represent the non-dimensional minimum, midpoint, and maximum values of the input variables ranges [72]. Each row represents a run for the given variable level settings with the last column representing the outcome (or response) of a simulation or an analysis code execution.

Table I: Typical Experimental Designs and Required Simulations

DoE	Simulations For 7 Variables	Simulations For 12 Variables	Equation
Full Factorial	2,187	531,441	3^n
Central Composite Design	143	4,121	$2^n + 2n + 1$
Box - Behnken	62	2,187	-
D - Optimal Design	36	91	$(n+1)(n+2)/2$

Table II: Face-centered CCD for 3 Variables

Case #	X_1	X_2	X_3	Response
1	-1	-1	-1	Y_1
2	-1	-1	1	Y_2
3	-1	1	-1	Y_3
4	-1	1	1	Y_4
5	1	-1	-1	Y_5
6	1	-1	1	Y_6
7	1	1	-1	Y_7
8	1	1	1	Y_8
9	-1	0	0	Y_9
10	1	0	0	Y_{10}
11	0	-1	0	Y_{11}
12	0	1	0	Y_{12}
13	0	0	-1	Y_{13}
14	0	0	1	Y_{14}
15	0	0	0	Y_{15}

There are two major limitations to RSM. RSM requires that the space under investigation must be homogeneous, either continuous or discrete variables. The other disadvantage is a limitation on the number of inputs allowed for model building. In general, a maximum of 8 variables is allowed for standard CCD and Box-Behnken designs. Due to the arduous task of creating statistically sound designs, there are no standard textbook DoEs for more than 8 variables. However, custom designs for more variables can be made as was done by Mavris [74] for 16 variables. In order to reduce the number of variables, another DoE, based on a linear model, may be used to estimate the main effects of each variable. The linear model is often referred to as an “effects screening test”. The screening test is a simpler DoE that utilizes a two level fractional factorial which tests the fit of a linear model, by accounting only for the variable main effects (i.e. no interactions), and allows for the rapid investigation of many variables to gain a first understanding of the problem. A regression analysis of this model, based on an Analysis of Variance (ANOVA) test, yields a Pareto plot that enables the identification of the most statistically significant contributors [45,70,72]. This linear DoE allows one to reduce the number of variables such that a second order DoE may be utilized with a smaller number of analysis executions.

A Pareto plot is a statistical quality improvement tool that shows frequency, relative frequency, and cumulative frequency of a set of variables to a response. It is in the form of a bar chart that displays severity (frequency) of a variable and is ordered from top to bottom in decreasing order. This allows the designer to decide which variables contribute to the response as seen in Figure 10. As can be seen, variable “X4” contributes approximately 32% to the response variability while all variables below “X15” have an

insignificant impact to the response. Usually, seven to eight variables will capture 80% of the response and in Figure 10, 4 of the 17 variables contribute to 80% while the remaining variable effects are minor. This result follows Pareto's Law, which states that "80% of the total of any group will come from only 20% of the components of that group." [24] Further, the "scaled estimates" provide the relative magnitude and direction of variable influence on the response. The 80% of the variables that do not contribute significantly to the response can be set at nominal values and remain constant, while the remaining 20% of the variables may be used with a higher order (i.e., three level) DoE to build the RSE. The Robust Design Simulation method discussed previously focused on maturing the use of RSM in aircraft feasibility and viability investigations.

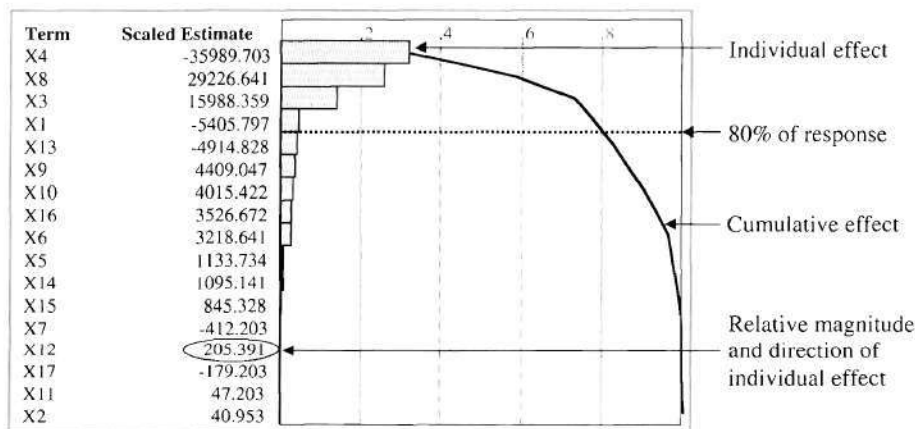


Figure 10: Example Pareto Plot

Commercial Software Facilitating RSM

The actual combination of cases, or simulations, that need to be tested can be found in various statistical textbooks or through the use of commercial statistical computer analysis programs, such as JMP® [75], Minitab [76], or iSIGHT™ [77]. JMP® is an easy to use interactive statistical graphics software package produced by the SAS Institute and

was chosen for this research. JMP[®] builds the DoE tables, regresses the data, performs the ANOVA, and provides graphical and statistical information regarding the selected model and is extremely suitable for the design problem under consideration.

One of the most valuable features of JMP[®] is its ability to instantaneously show how design variables affect one another. This is extremely useful in optimizing key variables using the RSM or *providing the decision-maker a visual means by which informed decision can be made*. One may change a key design variable and instantaneously see the effect on the responses. This is the Prediction Profiler feature of JMP[®]. An example Prediction Profiler is shown in Figure 11 and depicts the *prediction traces* for each independent X variable. The prediction trace is defined as the predicted response in which one variable is changed while the others are held at their current values, effectively, it shows the sensitivity of the response to the input variables. Moving the dotted line with the mouse varies the X variable and JMP[®] recomputes the underlying RSEs and updates the prediction traces and values, all in real time. Effects of the parameters in the prediction profiler are evaluated based on the magnitude and direction of the slope, where the “-1” and “1” values, shown above X_1 and X_2 , are normalized values with respect to the original dimensional ranges. The larger the slope, the greater the influence of a given parameter. If a parameter, listed on the abscissa, does not contribute significantly to the response listed on the ordinate, as “Y”, the slope is approximately zero. The sign of the slope, either positive or negative, depicts the direction of influence of the parameter. Furthermore, the limits of the metrics can be readily obtained by the upper and lower value of “Y”, shown as 50 and 100.

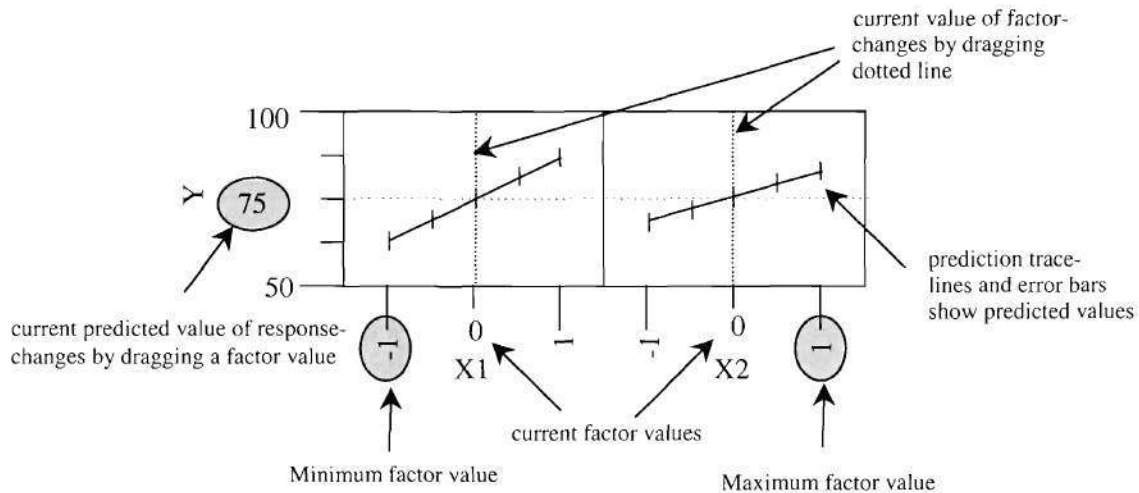


Figure 11: Example of a JMP® Prediction Profiler

Fast Probability Integration Background

The Fast Probability Integration (FPI) technique is embedded in the NESSUS (Numerical Evaluation of Stochastic Structures Under Stress) code and estimates the CDF that would result from a standard Monte Carlo Simulation approach. The NESSUS computer program [78], developed by researchers at the Southwest Research Institute (SwRI) for the NASA Lewis Research Center, is a probability analysis code based on the determination of a most probable point; an analysis concept frequently used in structural reliability analysis. The most probable point analysis utilizes a response function $Z(\mathbf{X})$ that is a function of several random variable distributions, including normal, beta, weibull, uniform, and so on. Each point in the design space spanned by the \mathbf{X}_i 's has a specific probability of occurrence according to their joint probability distribution function. Thus, each point in the design space corresponds to one specific response value $Z(\mathbf{X})$ which has a given probability of occurrence.

In cost analysis and other disciplines involving random variables, it is often desirable to find the probability of achieving response values below a critical value of interest, z_0 . This critical value can be used to form a limit-state function,

$$g(\mathbf{X}) = Z(\mathbf{X}) - z_0 \quad (2)$$

where values of $g(\mathbf{X}) \geq 0$ are undesirable. The most probable point analysis calculates the cumulative probability of all points that yield $g(\mathbf{X}) \leq 0$ for the given z_0 . Since the limit-state function “cuts off” a section of the joint probability distribution, a point with maximal probability of occurrence can be identified on that limit-state function. This point is called the most probable point. It is found most conveniently in a transformed space in which all random variables are normally distributed, as shown in Figure 12 [41]. Once the most probable point for a given probability is identified, the process can be repeated for several z_0 values, mapping each probability over the normalized distribution space to get a CDF. This CDF for $Z(\mathbf{X})$ can then be differentiated to obtain the probability density function (PDF) of the response. The FPI code offers several very efficient techniques that can approximate a Monte Carlo Simulation with a handful of analysis executions rather than the thousands of executions required for a typical Monte Carlo Simulation. An additional advantage of FPI is the fact that it wraps around an analysis code, eliminating the need for a metamodel, such as RSEs. However, the FPI technique does not provide a mathematical expression of the response as a function of the independent input variables.

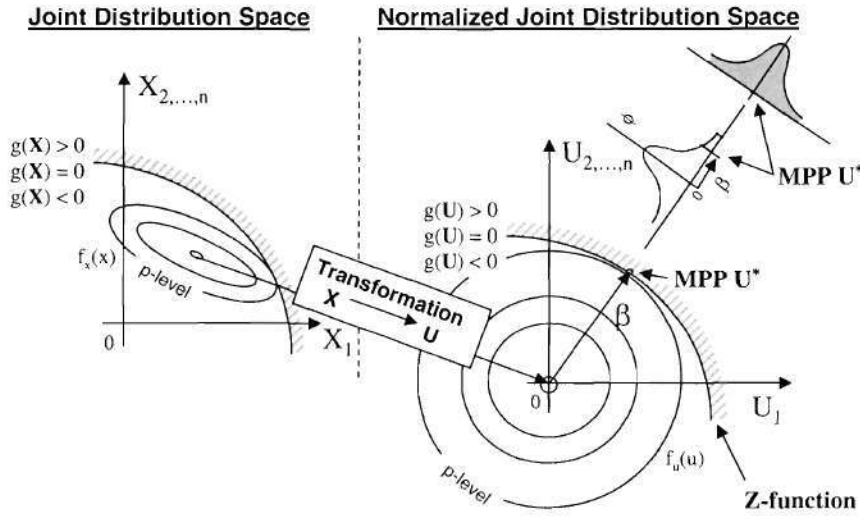


Figure 12: Most Probable Point Location [41]

Multi-Criteria Decision-Making Techniques

“Decision making, in general, and engineering decision making, in particular, often involve the balancing of multiple, potentially conflicting requirements. Classical optimization deals with these problems by taking the most important requirement as the objective function and the remainder as constraints.”[79] However, how does the decision-maker know a priori which is the most important requirement for a new design? In general, one does not know. One solution is to consider an alternative set of methods that allow for multiple criteria to be used concurrently in the decision making process. “These [methods] deal with multiple criteria problems as they appear and employ a range of processes [or algorithms] that clarify the consequences of the underlying trade-offs between criteria in configuring alternative solutions.”[79] These algorithms are called Multi-Criteria Decision Making (MCDM) techniques.

For clarity, a few MCDM definitions are needed [46]:

Criterion: A measure of value or effectiveness for an alternative

Attribute: A characteristic that describes, in part, the state of a product or system and provides a means of evaluating the levels of an objective

Objective: An attribute with a direction of desired change

Constraint: An attribute that has a threshold

Goal: A value or level of aspiration that is to be achieved, surpassed, or not exceeded

In general, MCDM techniques address multi-criteria problems from two view points, either product design or product selection. Hwang defines product design as being classified into the category of Multiple Objective Decision Making.

“Multiple Objective Decision Making is not associated with the problem where the alternatives are predetermined. The thrust of these models is to design the ‘best’ alternative by considering the various interactions within the design constraints which best satisfy the decision maker by way of attaining some acceptable levels of a set of some quantifiable objectives. The common characteristics of Multiple Objective Decision Making methods are that they possess a set of quantifiable objectives, a set of well defined constraints, and a process of obtaining some trade-off information, either implicit or explicit, between the stated quantifiable objectives and also between stated or unstated nonquantifiable objectives.”[46]

In contrast, product selection may be classified in the category of Multiple Attribute Decision Making (MADM) techniques. An abundance of MADM techniques have been created over the past 40 years to aid the decision-maker in identifying the best alternative amongst a finite set that maximizes customer satisfaction with respect to more than one attribute or criteria [35]. The best alternative is determined based on inter- and intra-attribute comparisons, which may contain explicit or implicit trade-offs for a given level of achievement.

Since optimization is not the focus of this research and design freedom leverage is desired as an element of the new paradigm, MADM techniques are more appropriate. For the reader's edification, Hwang [46] and Sen and Yang [79] describe various MODM methods in great detail. Only MADM techniques are discussed herein.

Multi-Attribute Decision Making Techniques

MADM techniques are product selection techniques in which the multiple attributes are processed to arrive at a single choice for the best product. Within the MADM category, the means by which the attributes are processed may be classified as noncompensatory or compensatory. Noncompensatory models do not allow for trade-offs between attributes and "comparisons are made on a criterion by criterion basis." [35] This category is not applicable for the current research since the aircraft design problem inherently involves trade-offs amongst attributes. In contrast, compensatory models do permit attribute trade-offs. With these models, a single number is usually assigned to each multidimensional characterization representing an alternative. Based on the manner in which this number is calculated, MADM techniques may be further decomposed into scoring models, compromising models, or concordance models [46].

Scoring models are based on the principle that the alternative with the highest score of a user-defined utility function is the best alternative. These models are popular for subjectively evaluating multiple objectives [80]. Some examples of scoring models include simple additive weighting and hierarchical additive weighting. Compromising models select an alternative that is closest to an ideal solution based on various algorithms and include TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and LINMAP (LINear programming techniques for Multidimensional Analysis

of Preference). Finally, a concordance model arranges a set of preference ranking which most satisfies a given concordance measure and include permutation method, linear assignment method, and ELECTRE (Elimination et Choice Translating Reality) [46].

Bandte provided an elegant MADM selection process that was a modified version of a process originally proposed by Sen and Yang. Bandte's process was further modified here to account for only the subjectivity inherent in the decision making process of product selection. That is, depending upon who the ultimate decision-maker is, the preference of which criterion is more important will change and should be implicitly accounted for. A modified version of Bandte's MADM selection process is depicted in Figure 13 and contains MADM techniques that are compensatory and allow for subjectivity in the selection process.

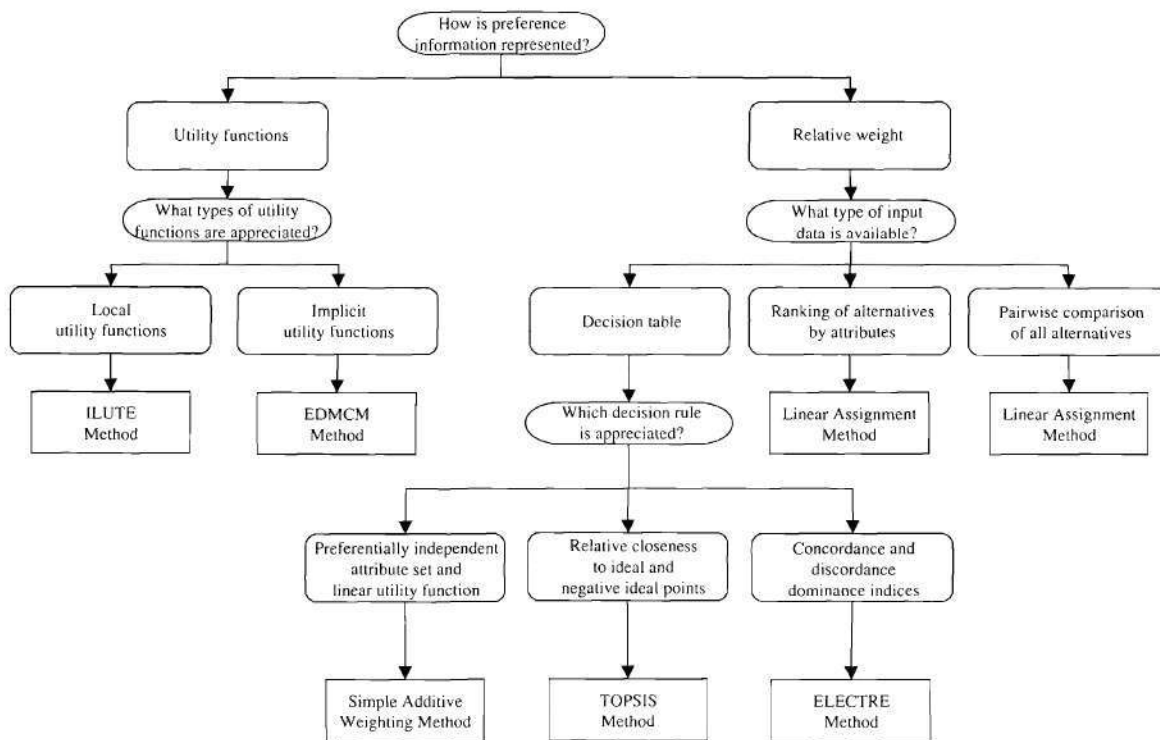


Figure 13: MADM Technique Selection Process

At the heart of most MADM techniques are the concepts of a Decision Matrix, DM, and an ideal solution, A^* . The DM is an m -by- n matrix of 'm' alternatives and 'n' criteria. A^* is a hypothetical solution based on the best achievement of all criteria, and in most situations, A^* is not a feasible solution contained in the original set of alternatives [67]. The best alternative is identified based on a multi-attribute utility function that is closest to the hypothetical ideal solution.

The use of MADM techniques for alternative (or product) selection has many advantages. The implementation is typically straightforward and easy to understand. Multiple objectives are accommodated with subjective weightings and risk is accounted for through subjective evaluation. Also, a great deal of insight can be provided to the decision-maker as to how the various concept alternatives compare to one another. Some of the disadvantages are that the outputs are not subject to rigorous defense and can therefore only be interpreted as relative measures. The resulting values have no absolute meaning in themselves and the problems tend to be oversimplified [80]. Finally, all MADM techniques require information in the form of point estimates about the criteria in the DM to find the best solutions.

Joint Probabilistic Decision Making (JPDM) Technique

The inefficiencies of the MADM techniques may be overcome with the use of the Joint Probabilistic Decision Making (JPDM) technique developed by Bandte [35]. JPDM is a rigorous mathematical approach that combines the "uncertain" customer requirements, each defined by a Probability Density Function (PDF), into a single objective called the joint Probability of Success (POS), a notion similar to Pareto Optimality [67]. The POS represents the probability of concurrently meeting all imposed

customer requirements that were subjected to design, operational, or technological uncertainty. The POS is determined from either an Empirical Distribution Function or a Joint Probabilistic Model [67].

Resource Allocation Approaches

“In successful organizations, strategic planning guides the decision-making process for all spending. Strategic planning can be defined as a structured process through which an organization translates a vision and makes fundamental decisions that shape and guide what the organization is and what it does.” Additionally, “leading organizations develop a decision or investment package to justify capital project requests. Although different organizations use different names for these decision packages – such as business cases or project requests – the packages generally include documents and analysis to support a proposed investment.” [81]

Unfortunately in the aerospace industry, traditional methods of investment in technology development programs or closing the business case are ad hoc and lack rigor. “Many R&D selection techniques have been developed in the last 30-40 years, but few have been used by R&D companies in industrial companies, in fact, the methods used aren’t much more advanced than two or three decades ago, even though the state of the art has advanced rapidly.”[82]

The allocation of resources considered herein is for technology development programs, not product development. “Product development entails the design and manufacture of a product, such as an airplane, a car, or a satellite, as an end item for delivery to a customer. Technology development fosters technological advances for potential application to a product development.”[83] Cetron observes five traditional approaches of allocating R&D resources for technology development [84]:

- 1) *Squeaking Wheel*: cut resources from every area and then wait and see which area complains the most. Based on the loudest and most insistent, then restore budget until ceiling is hit.
- 2) *Level Funding*: budget perturbations minimized and status quo maintained; if this approach continues within a rapidly changing technology field, the company, group, or agency will end up in serious trouble.
- 3) *Glorious Past*: “once successful, always successful”. Assign resources solely on past record of achievement.
- 4) *White Charger*: best speaker or last person to brief the boss wins the money or whichever department has the best presentation.
- 5) *Committee*: a committee tells the decision-maker how to allocate resources.

Cetron points out that the scientific and objective foundations of these approaches are lacking and naïve, but widely used. Thus, the business case that is developed is lacking in substance and strongly suggests the need for a means by which more informed decisions may be made. A primary focus of establishing the new paradigm methodology is the ability to infuse new technologies. Froham notes that most R&D technology developments are allocated resources based on past activities in the specific research area rather than the potential bottom line contributions [85]. In lieu of the traditional R&D allocation approaches, one should ask the following questions prior to committing scarce R&D resources [86]: Does the technology fit within the companies present and future business strategies and plans? Are the resources, both technical and monetary, available or accessible? Does the technology possess superior performance and/or economical characteristics of which commercial attractiveness is heightened? Will the resources spent on the technology development be recouped as profit when the technology is matured?

Modeling and Simulation Environment

In the conceptual stages of aircraft design, a rapid assessment is desired so that trade-offs can be performed with minimal time and monetary expenditures. The advent of the computer has greatly facilitated this objective. Presently in aircraft design, trade-offs are performed in a monolithic or legacy vehicle sizing and synthesis code that is multi-disciplinary (e.g., aerodynamics, structures) in nature. Yet the level of each disciplinary area is based on empirical relations derived from historical data of evolutionary concepts. If the designs of interest fall within this range, the legacy code can accurately assess the metrics. However, for a non-conventional concept, the level of confidence of the results will be questionable. The questionable results can be overcome through the direct linking of more physics-based analytical models or through the use of mathematical approximations (metamodels) to represent the physics-based analysis tool [87], thus replacing a given discipline deficiency. This process yields a preliminary design vehicle specific, synthesis and sizing tool. The use of a modeling and simulation environment is an essential element of the new paradigm. Since trade-offs and assessments are rapid, design cycle time is reduced, knowledge is brought forward through the linking of higher fidelity tools, and non-traditional disciplines can be integrated with ease.

For clarity, synthesis is defined as “the process of recomposing a system, previously decomposed for individual contributing analysis, based on a number of possibly coupled disciplines to form an integrated product”, while sizing is defined as “the specific mathematical algorithm that determines the size and weight of a vehicle based on a specified mission and contributing disciplinary analysis.”[40] The sizing of the vehicle begins with a definition of geometric, propulsive, and mission characteristics. Then, the

vehicle is 'flown' as a point-mass through a time-stepping procedure based on minimizing expended energy. At the end of the flight, if the fuel available is equal to the fuel required to fly the mission within some tolerance, the vehicle is said to be fuel balanced. Concurrently, the same balance is performed with the thrust. If the solution at the end of the mission does not balance, an iteration is performed with deviations of aircraft size to modify the available fuel and the available thrust.

Research Questions and Hypothesis

The challenge of the current research is to formulate a physics-based, system level, decision-making process that results in high quality, competitive cost products that satisfy future customer requirements. To accomplish this end, the method must address the system's life cycle, infusion of breakthrough technologies, and use of new design methods. In other words, a rapid, systematic, and methodical forecasting method is needed which can quantify performance, economic, and risk aspects of next-generation concepts and compare these results to future customer requirements. The method must be efficient to reduce design cycle time while capturing the impact of design decisions on the overall affordability of the system. This method must account for multi-criteria and constraint problems in the presence of operational and economic uncertainty, requirement ambiguity, and conflicting objectives. Furthermore, the process must allow for the infusion and subsequent affordability assessment of new, immature technologies while considering technological and economic risk. The generic framework proposed to achieve this goal is shown in Figure 14. The method begins with defining the problem and concludes with selecting the best family of alternatives responding to the customer

needs. The top-level questions that must be addressed to develop this framework into a specific method include:

What information is needed to accomplish each step?

What are the techniques, tools, or methods needed to execute each step?

What are the result, outputs, and information obtained from each step?

Is iteration necessary?

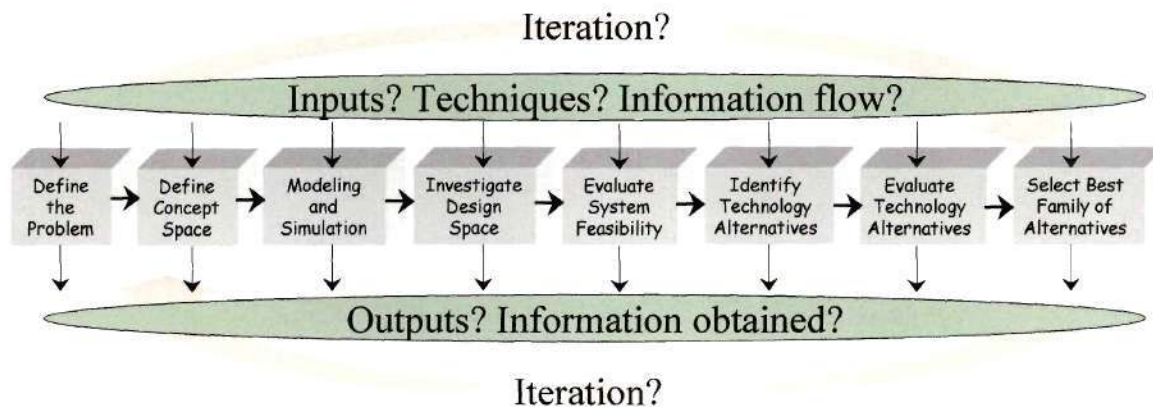


Figure 14: Generic Framework Needed for the New Paradigm

Additionally, to create the new design method, more detailed questions must be answered for each paradigm element:

Life Cycle Considerations:

How does one maintain design freedom leverage?

How does one optimally allocate scarce resources to maximize the ROI of a new product?

Breakthrough Technologies

How does one identify which technologies to infuse to the system?

How does one determine the maturity of a technology?

How does one determine the anticipated impact of a technology on the system so as to investigate the potential?

How does one model and assess the impact of an immature technology if a mathematical formulation does not exist and what are the consequences to the design in terms of performance, cost, schedule, and risk?

How does one identify which technologies, or mix of technologies, have the most impact and should be developed further?

New Design Methods

Which probabilistic design technique is the most appropriate?

How does one capture the multiple and conflicting customer requirements in the selection of a product?

How does one account for subjectivity in the selection of products?

Hypothesis: It is possible to create a rapid and efficient design environment that accounts for the inherent uncertainty associated with the early phases of design. The use of statistical and probability theories will enable the quantification of the design uncertainty. Further, it is possible to include the subjectivity of the decision making process through the inclusion of multiple criteria selection techniques. Finally, it is possible to quantify the impact of immature technologies in the conceptual phases of design through the use of forecasting and program monitoring techniques. It is assumed that the result of this approach will allow for increased knowledge, reduced committed costs, and increased design freedom leverage to produce high quality, competitive cost systems that meet aggressive future customer requirements in a systematic and comprehensive manner.

CHAPTER III

FORMULATION

The focus of the current chapter is to address the top-level questions regarding the generic framework for the new paradigm. Specifically, identify potential techniques and inputs needed to accomplish each step; identify the information flow; identify the results of each step that can be used in the decision-making process; and identify if an iteration is needed. As each step is developed, the more detailed questions posed regarding the three paradigm elements will be addressed. The result of this chapter will yield a potential design method that responds to the paradigm shift and is entitled the Technology Identification, Evaluation, and Selection (TIES) method.

Design Framework Development

Step 1: Problem Definition

The first step in TIES is to define the problem in terms of the customer requirements for which the product will be designed, the available budget to expend on the development, and the time frame in which the product must enter the market. In order to *formulate the problem, a customer or societal need must exist or a request for proposal*

must be stated to drive the design of a new product. This need is often termed the “voice of the customer” and is typically qualitative, or ambiguous, in nature. For example, a commercial airline performs a market study and identifies that a majority of potential passengers wish to have lower fares and more flight time options. These are subjective and qualitative “wants” that must be mapped into some economic, engineering, or mathematically quantifiable terminology.

A very efficient and organized technique for translating the “voice of the customer” to the “voice of the engineer” or designer is the Quality Function Deployment (QFD) process [30] extensively used in the IPPD approach described in Chapter II. The QFD concept was first introduced in 1972 in Japan and has been used in the U.S. since 1983 in the electronics and automotive industries as a means to “increase customer satisfaction while reducing the cycle time of product development.”[30] With this process, the qualitative needs and requirements are mapped into system attributes. These attributes can be ambiguous (passenger seat comfort), uncertain (daily cost of fuel), and/or deterministic (design range). For the example of more flight time options, the mapped voice of the customer would be a higher utilization which implies a higher vehicle availability and, hence, component reliability. From the QFD process, the customer requirements, or customer-supplied wants that must be fulfilled, are established.

For a commercial system, the definition of the customer requirements must capture the needs of the airframe and engine manufacturer, airlines, airports, passengers, and society as a whole through operational and environmental regulations. The requirements may be objectives or constraints and in the context of this research will be defined as system metrics, or a system attribute that is tracked for the purpose of decision-making.

In essence, the system metrics are the thresholds by which the system under consideration can be measured as successful. If the system can meet all imposed metric thresholds, then the system should be considered for launch, else, the program should be cancelled or an alternative system considered.

In addition to the customer requirements, market studies will provide a target date that the product needs to Enter Into Service (EIS). The EIS date will drive the development schedule. Additionally, the management will provide the decision-maker an allowable budget to invest in the program development. As noted by Dillon, meeting the schedule and budget constraints in many aerospace programs has been a difficult challenge [8].

Step 1 Summary:

Inputs: societal need as a result of market studies

Techniques: QFD and brainstorming

Outputs: specific customer requirements for which the design will be judged,
program budget, anticipated EIS date

Step 2: Define Concept Space

Once the customer requirements are defined in terms of *quantifiable* engineering parameters, the thrust of the TIES method begins with the definition of the concept space and is driven by innovation and “out-of-the-box” thinking. Initially, the experience, knowledge, and intuition of the designer is utilized to identify a potential class of vehicles and provides the methodology with a starting point for selecting potential solutions to satisfy the customer requirements. The focus of this step is two-fold: identify the space of

alternative concepts that is based on a defined class of vehicles, and establish the geometric and propulsive design space for which system feasibility is initially sought.

Define Alternative Concept Space

In the design of any complex system, there exists a plethora of combinations of particular subsystems or system characteristics that may satisfy the problem at hand. For example, how many engines are needed? What type of high lift system is needed? Is a horizontal stabilizer preferred over a canard? A functional and structured means of decomposing the system and identifying component options is through the use of a Morphological analysis as pioneered by Fritz Zwicky [88]. A Morphological analysis aids in the creative process of generating alternatives and may be classified as two types: ordered and random [89]. The latter is indicative of brainstorming and the former is structured in a matrix. This matrix aids the decision-maker or designer to identify possible new combinations of subsystems to meet the customer needs [37]. The Morphological Matrix is formed by identifying the major functions or characteristics of a system on the vertical scale and all the possible alternatives (or system attributes) for satisfying the characteristics on the horizontal scale. In essence, this is where mature and immature technology alternatives are defined. Once the matrix is populated, an alternative design concept is defined as a mix of the characteristic alternatives. All possible design alternative combinations define the *alternative concept space*. In general, one alternative concept is established to begin the feasibility investigation and will be called the *baseline concept* and is typically drawn from mature or present day technologies. A Morphological approach to generating design alternatives is best understood through example.

An example Morphological Matrix for a pen is depicted in Figure 15. Some of the characteristics that define a pen include the type of casing, the writing tip, the color, and the line width. The alternatives to satisfy the pen characteristic of line width include fine, medium, and heavy. Once the matrix is populated with all possible characteristic alternatives, a design alternative concept may be defined as a specific list of characteristic alternatives. As in Figure 15, the circled items denote the combination of various alternatives of which comprise a single concept. The circled characteristics define a ballpoint pen that has a metal casing and writes a *medium* black line. Another concept alternative would be a ballpoint pen that has a metal casing and writes a *fine* black line. Thus, other combinations of characteristic alternatives constitute the concept design alternatives. No limit should be placed on the number of alternatives, nor should the alternatives exclude exotic ideas. The Morphological Matrix is a technique to spur creativity and outside the box thinking.

	Alternatives		
	1	2	3
Casing	Plastic	Metal	Hybrid
Writing Tip	Felt	Ball	
Color	Black	Red	Blue
Line Width	Fine	Medium	Heavy

Figure 15: Example Morphological Matrix

Define Design Space

Once the baseline concept is defined from the alternative concept space, the baseline may be further decomposed into product and process characteristics. This can be performed via a Morphological Matrix or through brainstorming sessions with IPTs. Primary product attributes include the physical design parameters that describe a

characteristic of the system. For the pen example, product attributes of the casing would be the length, the weight, and the diameter. In conceptual and preliminary aircraft design phase, all of the design parameters should not be fixed but should vary within some specified range until such time as a configuration is “frozen”. The process attributes include certification, manufacturing, economic, and operational parameters, which are inherently uncertain.

Within the context of TIES, the product attributes are the key design variables (with associated ranges) which define the design space of interest for a given alternative concept. These design variables are often referred to as “control” factors, or variables that are within the designer’s control [41]. These key design variables, and associated ranges, define the design space in which system feasibility is sought. The design variable ranges are chosen such that the largest possible deviations in the given baseline configuration may be captured. However, the design variable ranges must be able to have a converged solution, that is, be capable of flying the specified mission and have a continuous design space. Care should be taken so that a handful of variables do not artificially dominate the design space due to larger relative ranges. For example, if one variable is allowed to deviate $\pm 5\%$, other variable deviations should be the same order of magnitude.

Step 2 Summary:

Input: class of vehicle

Techniques: brainstorming and Morphological analysis

Outputs: Morphological Matrix defining the alternative design space, baseline concept definition with an associated design space

Step 3: Modeling and Simulation Environment

As described in Chapter II, a modeling and simulation (M&S) environment is required to facilitate rapid assessments with minimal time and monetary expenditures of the alternative concepts (and associated design space) identified in the Morphological Matrix. Although an M&S environment is needed all throughout the TIES method, this step follows the “Define Concept Space” so as to properly identify the capabilities needed for the M&S environment. The Defense Systems Management College defines a model as “a physical, mathematical, or logical representation of a system entity, phenomenon, or process”, while a simulation is “the implementation of a model over time...and a simulation brings a model to life and shows how a particular object or phenomenon will behave”. [90]

Most companies have an in-house developed M&S environment to perform the design trades. However, *the TIES method is not code specific or system specific*, but, the M&S tool utilized must have some basic features as outlined in Table III. One cannot underestimate the importance of having a cohesive M&S environment. Without this environment, application of the TIES method is arduous and would be qualitative in nature. A principle requirement for any decision making process is the ability to quantitatively assess the customer requirements that drive a design. This can only be achieved through an M&S environment. In fact, the Defense Systems Management College states that use of an M&S environment provides four benefits to the design process and includes cost savings, accelerated schedule, improved product quality, and cost avoidance [90].

Table III: Required Features Needed for an M&S Environment

Feature	Importance	Purpose
Parametric inputs	<i>High</i>	To quantify outputs in terms of inputs and facilitate the use of Response Surface Methods
Physics based	<i>Very High</i>	To analyze and model evolutionary or revolutionary concepts based on desired fidelity and operational environment
Synthesis capability	<i>Average</i>	To quantify the various disciplines (aerodynamics, structure, and propulsion) for a given configuration or could use table look-ups created off-line
Unconstrained mission analysis	<i>Very High</i>	To “size” the system from an algorithm based on physical principles for a given system and provide responses, or customer requirements, in an unconstrained manner so as to employ the use of metamodels
Robust input definition	<i>High</i>	To allow for a wide range of configurations or missions to be analyzed
Economic analysis	<i>Very High</i>	To immediately quantify the impact of design changes on the economic requirements of the system
Quantifiable responses	<i>Medium High</i>	To functionally relate the responses of interest to the variations of inputs
Disciplinary technical metric impact factors	<i>Very High</i>	To simulate the discontinuity associated with the addition of new technologies, also called technology “k” factors
Automation capability	<i>Average</i>	To facilitate probabilistic design methods and to have a “wrapper” around the tool
Rapid Assessments	<i>Average</i>	To facilitate reduced cycle time
Access to source code	<i>Average</i>	To modify fidelity or physical principle deficiencies of different disciplines as needed and understand internal control laws or to add technical metric “k” factors

A few issues regarding the M&S environment must be addressed to properly implement the TIES method, in particular, a more detailed discussion of the features rated with a “very high” importance. First, a physics-based analysis is essential to accurately model the designs of interest. This implies that the level of fidelity desired by the decision maker must be reflected in the analysis. For example, if one were to consider a derivative of a commercial transport, the analysis of the design must be able to capture, within the desired fidelity, all of the pertinent customer requirements. Thus, the physics governing the evaluation must model the aerodynamics, propulsion, and structures of a subsonic vehicle. If a supersonic vehicle is of interest, the M&S environment must be able to capture the physics associated with supersonic flight. Additionally, if the design were of a hypersonic vehicle, a different set of governing equations must be used. The designer must take into consideration what physics are required to accurately assess the system when creating or identifying the proper M&S environment. Thus, the needed capabilities are problem dependent and should be determined based on the system under consideration and in some instances, may need to be created from scratch.

Along these same lines, if a revolutionary technology is under investigation, the behavior of the system or the technology must be physically quantifiable or estimable. Situations may arise when the benefit of a technology changes the system so drastically that the underlying physics may break down and require a new set of physical principles. Thus, the designer must take into consideration how the system might change as a result of infusing a revolutionary technology and have the appropriate switches, internal to the tool, to capture the physics.

The unconstrained mission analysis is an important feature required if the Response Surface Methodology (RSM) is to be utilized. As discussed in Chapter II, RSM approximates the dependency of output metrics to input parameters with an empirical polynomial relationship. In general, the approximation is a second order Taylor series model. An assumption made with the RSM approach to model building is that the input parameters are *continuous*. Thus, if the input to the analysis, based on the Design of Experiments, is modified from the original setting, the accuracy of the resulting model and response behavior would be in question. The modification of an input parameter would occur if the governing equations of the sizing or synthesis algorithm had constraint values, such that the input value was reset or changed to a value other than that which was input during the execution.

The modification due to an internal constraint may originate from limitations of physical principles. For example, an input to an analysis tool may be the inlet temperature to the engine turbine. If the temperature value input to the tool exceeded the allowable temperature of the blade materials, a limitation would be imposed with the intention that the blades do not melt and the input value adjusted to compensate. The physical limitation, or constraint, imposed on the analysis would skew or bias the output results. Although this is the appropriate engineering approach, limitations of this nature may inhibit application of the RSM. A potential solution for this dilemma would be to modify the analysis tool to provide an error message when a physical limitation was violated and state that the results are not physically realizable. At that time, the decision-maker could modify the analysis capability to handle the physics of the problem under investigation or adjust the assumptions of the investigation.

Next, as discussed in Chapter I, the ability to quantify design changes on the economics of the system is very important, since a key driver for the success of any new design is a measure of the system's affordability. Thus, a means to quantify the affordability as a function of varying design configurations must be created. The economics of an aircraft system are essentially the life cycle costs. The life cycle costs are a summation of the Research, Development, Testing and Evaluation (RDT&E), acquisition price, operation and support costs, and disposal costs. Two approaches to quantifying the RDT&E costs and acquisition price include the use of cost estimating relationships and activity-based costing. The former approach is based on historical trends of component costs as a function of component weights, while the latter is based on the cost of the specific activities associated with the design and production of the system. On the other hand, the operation and support costs are determined based on the acquisition price, stage length, utilization, tax and interest rates, and desired yields over the life of the system. There are many approaches for the determination of operation and support costs, but an ability to quantify the costs must exist to properly capture the operator's expenses and revenues (if applicable) of the system.

Finally, since breakthrough technologies will be infused to the system of interest, an ability must exist to quantify the technology impacts. A standard practice for modeling technologies in the aerospace industry is through incremental changes in disciplinary metrics such as drag, component weights, and fuel consumption within a M&S environment. The incremental changes are determined from more detailed, higher fidelity analysis or experiments at the disciplinary level and rolled up to the system at the decision makers level. The incremental changes simulate the discontinuities associated

with the addition of new technologies. Thus, to model the incremental changes of the disciplinary metrics, a multiplicative factor on those metrics must be added within the synthesis or sizing algorithm. Most analysis tools already have these factors built into the source code as calibration factors. However, if the factors are not inputs to the tool, the internal logic must be modified such that the factors can be input directly.

Step 3 Summary:

Inputs: level of confidence or direct linking of higher fidelity analysis tools, design space parameters and disciplinary technical metric “k” factors

Techniques: physics-based design simulation environment

Outputs: quantified customer requirements

Step 4: Investigate the Design Space

With the design space and customer requirements defined and an M&S environment created, the design space exploration commences. This step begins with the establishment of datum values for all customer requirements (system metrics) identified in Step 1. The design space (represented by the design parameter variation) of the baseline configuration is initially investigated and the associated metrics quantified. Similar to the aircraft characteristics in the Morphological Matrix, there exists an infinite number of design variable combinations or settings. At the outset of a design process, no preference should be made as to what the particular vehicle *should* look like and the entire design space should be investigated. The probabilistic methods discussed in Chapter II may facilitate the design space investigation. Although design variables are in fact control variables, they may be “represented” as noise variables so as to utilize a probabilistic design

approach to rapidly assess and visualize the entire design space. As discussed previously, there are three methods by which the design space may be investigated:

- 1) Linkage of an analysis code with a Monte Carlo Simulation
- 2) Linkage of a metamodel of an analysis code with a Monte Carlo Simulation
- 3) Approximate the Monte Carlo with a Fast Probability Integration technique

The first method is the most accurate and most computationally intense since the analysis tool is executed directly, but is preferred if the analysis tool executes rapidly. The second method uses a particular metamodel called a Response Surface Equation (RSE), based on the Response Surface Methodology (RSM) discussed earlier, to approximate the analysis tool and a Monte Carlo is performed on this equation. The efficiency of this method is limited to the order of the approximation and the number of variables considered [74]. The third method is to use the FPI technique to approximate the response CDFs. FPI approximates the CDF of the metrics directly using the analysis tool (as a “wrapper”) and requires fewer simulations than an RSE.

Which technique is more appropriate for investigating the design space? The answer to this question is problem dependent. Hence, it is the decision-makers prerogative as to which technique to employ and the execution speed of the M&S environment. As a guideline, Table IV lists aspects of a given problem to guide the selection of the appropriate technique. The decision-maker should use intuition or experience as to how the system may behave or how rapid the analysis execution is to select the correct technique. If execution is rapid, Method I could be used. However, if no knowledge exists about the system in question, Method II should be used since more

information and flexibility are provided as a result of the application. The procedure to investigate the design space is:

1. Select one of the three methods
2. If Method II is chosen and more than 16 variables describe the design space, perform a screening test to identify the most relevant variables
3. Define the input parameter shape distributions (for design variables, these should be uniform to allow for an equal occurrence of each setting)
4. Execute the method
5. Extract the metric or response probabilistic results, either in PDF or CDF form

Table IV: Comparison of Probabilistic Design Methods

Aspects of the Problem	Method I	Method II	Method III
Number of simulations	Very high	Moderate	Few
Set up time	Moderate	Moderate to high	Low
Run time	Very high	Moderate	Low
Number of allowable variables	Unlimited	≤ 16 , can down-select with a screening test	≤ 100 , only limited by array dimensions
Accuracy	Exact	Good with correct choice of DoE and moderate variables interactions	Good if $\leq 2^{\text{nd}}$ order effects and no strong interactions between variables
Functional relationship between response and variables	No	Yes	No
Response sensitivity to independent variables	No	Yes	No
CDF sensitivities to independent variables	No	Yes	Yes
Ability to handle <i>strong</i> variable interactions	High	Moderate	None
Robustness to change in assumptions	Low: must repeat the entire approach	Moderate to high	Low: must repeat the entire approach
Information obtained	Low	High	Low

If Method II is utilized to investigate the design space, statistical software, such as JMP®, should be utilized to build the DoE tables, regress the data, and perform the ANOVA. If JMP® is utilized, one of the most valuable features is the prediction profiler. Thus, if the design space is investigated with Method II, the profiler is a fallout of the approach and the information obtained regarding the design space is enormous. The information includes the sensitivity and direction of influence of each design variable on the responses, the upper and lower limits of the responses and also the design space, and an environment whereby the design may be optimized as discussed in Chapter II.

Step 4 Summary:

Inputs: design variable shape distributions, baseline configuration

Techniques: probabilistic design approach is wrapped around the M&S environment

Outputs: response probabilistic data (CDFs or PDFs), prediction profiler (only Method II) which provides functional relationships of responses, sensitivities, and bounds of the design space

Step 5: Evaluate System Feasibility

The goals of Step 5 are:

- *To identify how feasible the design space is*
- *To identify where the design space lies in relation to the constraints*
- *To identify which constraints are “show-stoppers” or are inhibiting acceptable levels of feasibility*
- *To provide guidance as to the magnitude and direction of needed improvements to obtain an acceptable feasible space*

To quantify the system feasibility, the decision-maker has two options. First, as the Monte Carlo Simulation is executed in Method I or Method II of Step 4, one could simply count the total number of configurations that can satisfy all metric constraints and divide by the total number of simulations. Bandte notes that this approach empirically collects data samples to determine the cumulative probability function such that the percent feasible space is defined as:

$$POS = \frac{1}{M} \sum_{j=1}^M I(\mathbf{z}_{\min} \leq \mathbf{z}_j \leq \mathbf{z}_{\max}) \quad (3)$$

where POS is the Probability Of Success of satisfying the vector of criteria, \mathbf{z}_j , falling in the feasible range between \mathbf{z}_{\min} and \mathbf{z}_{\max} for M number of simulations [35]. If the percent feasible space is equal to 0 (POS=0%), one or more of the metrics cannot be satisfied simultaneously with the other metrics within the current design space and assumed technology level. To establish the concept “show-stopper(s)”, one must evaluate each individual metric CDF.

This approach does not work when Method III (FPI technique wrapped around the analysis tool) is used. The output from Method III is only the individual metric CDFs (not a joint formulation) for a limited number of simulations. An accurate representation of the POS increases with the number of simulations. Hence, the alternative approach for evaluating the system feasibility is to inspect each metric CDF at the outset. Based on the constrained metrics identified in Step 1, the decision-maker must establish the acceptable probability level for each metric CDF, as depicted in Figure 16. For each metric CDF, the target value is overlaid and the intersecting probability level is read off the plot.

What is the significance of the probability values? If a metric has an 80% probability (or confidence) of achieving the target, the design space available for optimization or deviation is plentiful and the design freedom is heightened and considered acceptable and robust. Yet, a low probability, $P < 5\%$, of achieving a solution that satisfies the metric constraints implies that little room exists for geometric or disciplinary optimization and a means of improvement must be identified. The feasibility limits – upper and lower – of acceptable, marginal, and unacceptable are purely subjective limits that the decision-maker may impose. Yet, the larger the feasible space, the more robust the designs are to changes in customer requirements.

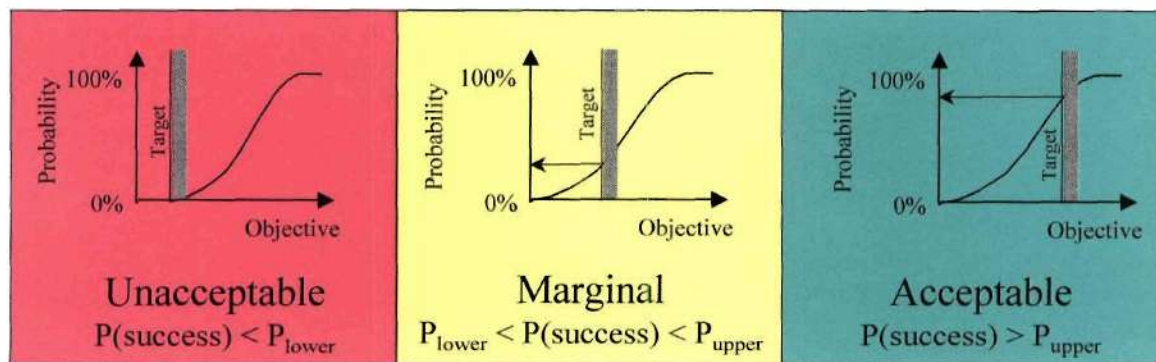


Figure 16: System Feasibility Levels

If the amount of feasible space is unacceptable to the decision-maker, there are four options:

- 1) Widen the design variable ranges to increase the design space and potentially capture feasible solutions
- 2) Relax the constrained metrics through customer negotiations
- 3) Select a different concept space or class of vehicles
- 4) Infuse new or advanced technologies

If the design space was properly defined at the outset, option 1 is not a choice. Also, relaxing the constraints is not a choice if any of the metrics are regulatory or operational constraints imposed by a government entity, such as the Federal Aviation Administration (FAA). These are non-negotiable, rigid constraints. Selecting a different concept space is an option but is not pursued within the context of this research. The last option, infuse new or advanced technologies, is the impetus for this research.

There exist two avenues by which technologies may be infused into the system. One is to look forward and the other is to look back as depicted in Figure 17. If the decision-maker deems that the system is not feasible today in comparison to the targets set for the future, the following questions may be posed. *What will it take me to do today to get where I want to be in the future? Or, with the specific technologies that I have today, where will I be in the future?* The first avenue is a method that has been developed and applied to various vehicle concepts [41,91,92] and is called Technology Impact Forecasting (TIF). The latter method is the focus of this research and is the TIES method. As will be shown in Chapter IV, TIF is a fallout of applying TIES.

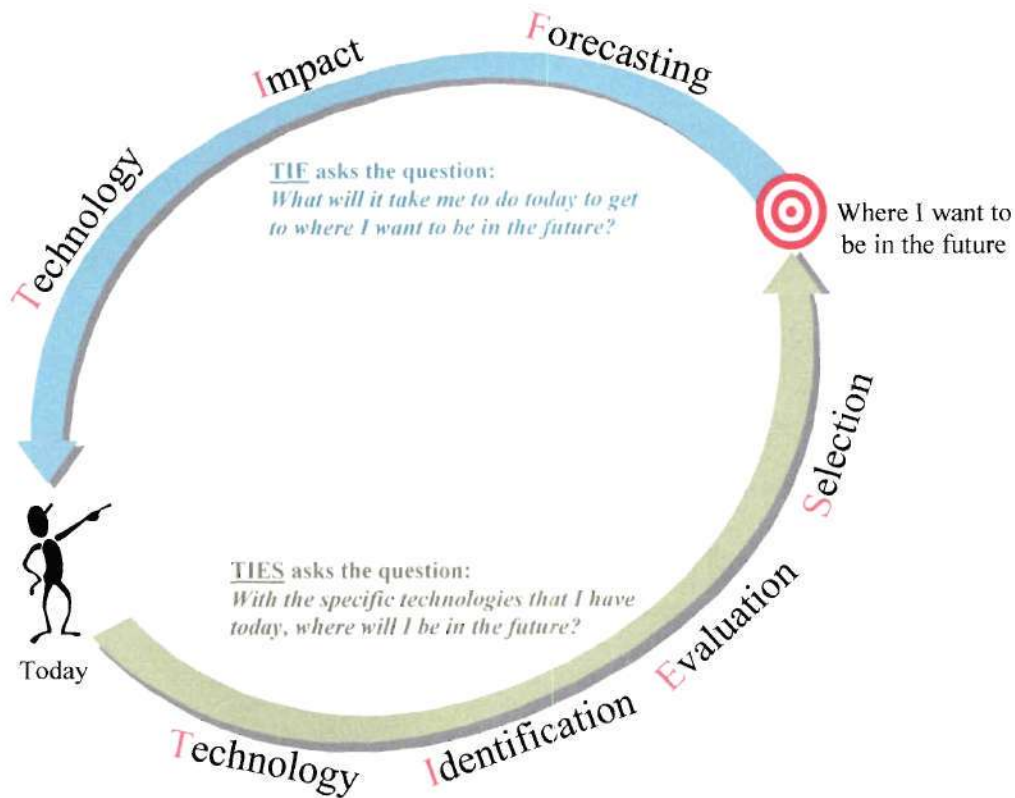


Figure 17: Avenues for Infusing New Technologies

Step 5 Summary:

Inputs: metric CDFs or PDFs, level of confidence, constraint values

Techniques: POS or visual inspection

Outputs: system feasibility levels, concept “show-stoppers”, amount of needed improvement for feasibility

Step 6: Technology Identification

To overcome the “show-stopper” metrics or to improve the current system, specific breakthrough technologies must be infused. This is the heart and soul of the TIES method. To accomplish this end, applicable technologies or programs must be identified from the Morphological Matrix of the alternative concept space defined in Step 2. The

selection of the technologies should be guided by the troubled metrics identified in Step 5 and also any other potentially enabling technologies that may indirectly improve the system. Once the set of technologies is identified, the following must be addressed.

Are the technologies physically compatible?

What is the impact to the system from each technology?

What is the readiness, or maturity, of each technology?

Technology Compatibility

Once the appropriate technologies have been identified, physical compatibility rules between technologies are established and formalized in a Technology Compatibility Matrix (TCM). This matrix is best prepared by a group of technologists or disciplinary experts familiar with each of the selected technologies. The purpose of this matrix is to eliminate combinations that are not physically realizable and, as a by-product, results in a downsizing of the evaluation problem. Incompatibilities arise when technologies are competing for the same application or one technology severely degrades the intended function or integrity of another.

An example TCM is depicted in Figure 18 for three arbitrary technologies (T1,T2,T3) where a “1” implies compatibility and a “0” implies incompatibility. It should be noted that the limiting case of compatibility is assumed to be a combination of two technologies. This implies that if two technologies are not compatible, then adding another technology, which may be independently compatible with the others, will not change the compatibility of the first two - the mix of the three would still not be compatible. In this matrix, T1 and T2 are not compatible. As an example of functional

degradation, a composite wing structure could not have a hybrid laminar flow technology. Due to the nature of composite structures, the micro-holes needed for the boundary layer suction of hybrid laminar flow control would severely compromise the composite matrix and create structural integrity problems.

Compatibility Matrix (1: compatible, 0: incompatible)			
	T1	T2	T3
T1	1	0	1
T2		1	0
T3			1

Figure 18: Example Technology Compatibility Matrix

System Impact of Technologies

Unfortunately, advanced technologies are difficult to assess within a conceptual M&S environment such as a sizing and synthesis tool. A formulation of a technology in terms of elementary variables does not lend itself to an M&S environment. Sizing and synthesis tools are typically based on regressed historical data that limits or removes their applicability to exotic or revolutionary technologies, and, if the technology is in its infancy stages of development, a closed-form mathematical model probably does not exist. However, introducing technology impact factors (“k” factors) can quantitatively assess the impact of a technology as was described previously. These “k” factors modify disciplinary technical metrics, such as specific fuel consumption, cruise drag, and/or component weights that result from a sizing tool. In effect, the “k” factors simulate the discontinuity in benefits and/or penalties associated with the addition of a new technology within the M&S environment so that rapid assessments can be performed.

For example, an arbitrary technology (T1) is expected to reduce cruise drag by 10% ($k_{\text{drag}} = -10\%$) while increasing Operation and Support costs (O&S) by 3% ($k_{\text{O\&S}} = +3\%$). Thus, a vector of “k” factors can be defined for each technology whose elements consist of the benefits and penalties associated with the technology. Each element of the vector has an estimated impact value as established via expert questionnaires, literature reviews, or physics-based modeling [93] and is based on the upper limit of where the technology *should* be when maturity is reached. Not all technologies will affect each element of the vector, but the vector must capture all the metrics that the technologies influence for evaluation purposes.

The technology vectors can be combined into a Technology Impact Matrix (TIM). An example matrix for three technologies that influence four technical metrics is shown in Figure 19. In this example, T1 and T3 affect all “k” factors except for the second, while T2 does not affect the first or third. A disciplinary metric reduction is represented as a negative percentage (-%), an increase is a positive percentage (+%), and present day technologies are no change (0% or ~), where present day technologies implies the current state-of-the-art. The vector *must* include benefits *and* degradations to accurately assess the impact of technologies. The identification of the appropriate form of the technological uncertainty modeling for a given TRL is discussed in Chapter IV.

		Technologies Considered		
Disciplinary Metrics		T1	T2	T3
	k factor 1 (O&S)	+4%	~	-10%
	k factor 2 (Drag)	~	-3%	~
	k factor 3 (RDT&E)	-1%	~	-2%
	k factor 4 (Fuel burn)	-2%	-2%	+3%

Figure 19: Example Technology Impact Matrix

As stated above, the impact that each technology has on the system may originate from three sources: expert team questionnaires, physics-based modeling, or literature reviews. Each source of impact estimation has an associated uncertainty. In some cases, this uncertainty is not quantifiable. For example, if one was to ask an aerodynamics expert how much drag reduction would result from the addition of a laminar flow technology to a vehicle, the answer would be subjective and based on the experience and knowledge of that expert. Furthermore, the expert's estimate may be based on a disciplinarian's point of view without knowledge of other discipline limits unless iterative schemes of information flow between experts exists. This iterative scheme is costly and time consuming, and decisions and information are usually lost.

Next, uncertainty is also associated with estimates stemming from physics-based modeling. This arises from the fidelity of the analysis tool utilized (panel code versus Navier-Stokes code), geometry modeling (flat plate versus full three-dimensional), and the assumptions around the analysis (point mass flight simulator versus six degree of freedom model). Finally, if a literature review is the only means of quantifying the impact of a technology, the issue of applicability across classes of vehicles is posed. If a

technology has matured on one system, can one apply the same impact to another, different type of system? Furthermore, if the literature review is of an immature technology, the two previous issues apply. A primary, underlying theme associated with each source of impact uncertainty is the maturation level (or readiness) of the technology. This aspect of the TIES method is subsequently addressed.

Technology Readiness

In general, the impact of a technology is probabilistic in nature. The probabilistic nature arises from various contributing factors, especially if the technology has not fully matured, i.e. widespread commercial or military application. Hence, an understanding is needed on the unique aspects of an immature technology, in particular:

- 1) The milestones encountered during a generic technology development program,*
- 2) The sources of uncertainty during that development, and*
- 3) The potential methods for bounding and forecasting the uncertainty to quantify the impact.*

Technology Development and Uncertainty

The innovative process by which a technology is developed can be qualitatively described through a monitoring of the major milestones achieved from concept formulation to widespread application. As defined by NASA for application in the aerospace community, the milestones have been characterized into a metric known as the Technology Readiness Level (TRL) [34]. A description of the NASA defined TRLs is listed in Table V. The TRLs represent a checklist for monitoring the progress of a *successful* technology program and the expected impact. A successful program is one that

can achieve all goals within the allowed budget and schedule. Consideration is not given to disruptive events that may alter the progression such as schedule, budget, market demand, political or socio-economic policy, or physical limitations. The TRLs simply describe the maturation and development process of a technology and provide a basis by which different technologies can be compared as they progress through the gates of maturation. Martino points out similar milestones for generic development programs but includes commercial introduction or operational use, widespread adoption, and diffusion to other industries past the TRL=9 level [27]. For program monitoring, TRLs are appropriate, but should be mapped to a quantitative scale for the purpose of decision making. To do so, one must understand how a generic technology develops and matures.

Table V: Typical Technology Readiness Levels

Level	Readiness Description
1	Basic principles observed and reported, paper studies
2	Technology concept and/or application formulated (candidate selected)
3	Analytical and experimental critical function or characteristic proof of concept or completed design
4	Component and/or application formulated
5	Component (or breadboard) verification in a relevant environment
6	System/subsystem (configuration) model or prototype demonstrated or validated in relevant environment
7	System prototype demonstrated in flight
8	Actual system completed and flight qualified through test and demonstration
9	Actual system flight proven on operational vehicle

“No single growth pattern describes the development and diffusion of all technologies. There are general concepts of how technologies develop, however, and these can be a useful guide.”[94] One of the prominent concepts is through the *method of analogy* to other well-known physical or biological systems such as growth patterns of yeast cell populations [39]. Historical data for various technology concepts, including aircraft speed, steam engines, and fluorescent lamps [27], has revealed an ordered pattern of development that resembles this biological growth curve, also known as a sigmoid curve or an S-curve. The method of analogy assumes that a technology development program will follow this S-curve pattern *if a successful program is achieved*. An example S-curve growth pattern is shown in Figure 20 [94].

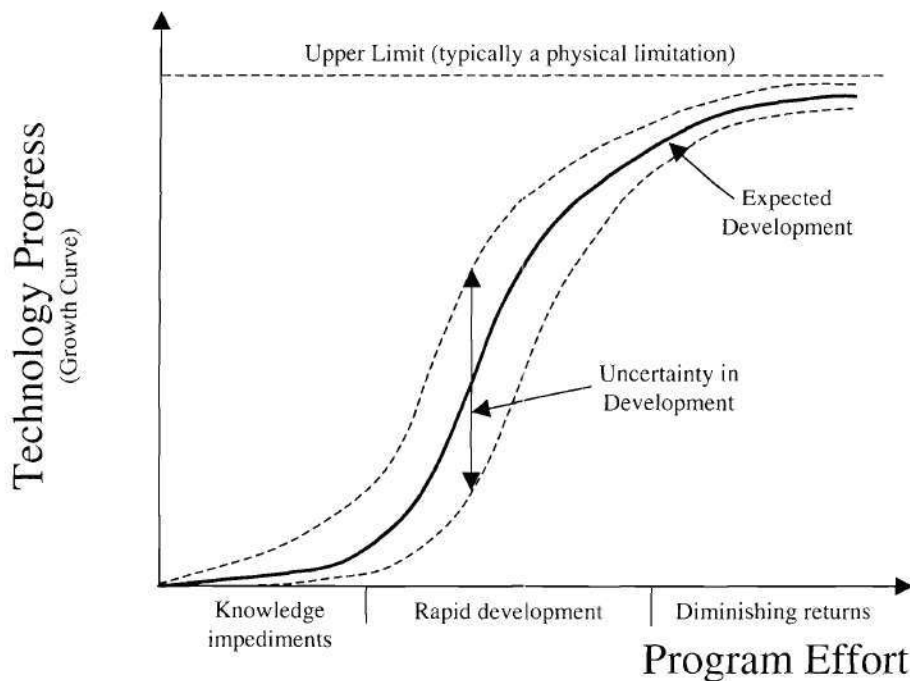


Figure 20: Generic Technology Development

The solid S-curve is the expected or ideal progression of a technology as a function of program effort, where program effort is dependent on monetary resources, manpower, and computational and physical testing. Porter observed that the program advances “slowly as many impediments must be initially overcome, advances rapidly for a period and then slows as the easy improvements” are achieved [94]. The uncertainty bounds associated with the expected maturation curve are due to variations in knowledge, schedule, budget, available resources, and integration difficulties, in addition to assumptions made and models used to analyze and design the technology. As would be expected, the uncertainty diminishes as the program advances and knowledge and experience increases. The upper limit of this curve is typically viewed as a physical limitation of the functional capability of the technology and in most instances, a point of diminishing returns and technology obsolescence. In a successful program, the upper limit is analogous to the impacts estimated in the TIM.

Based on the concept of the technology progress curve and the TRL definitions, a quantitative scale for measuring technology maturity is desired. Yet, one issue arises immediately. The NASA TRL descriptions from 1 to 5 are based on the component development milestones, such as a combustor or high-lift system. At a TRL of 6, the component is integrated to the system and the milestones continue from there. Typically, a technology is developed for a given component, e.g. a new combustor, new materials for the wing, or new control systems. The technology development and shrinking uncertainty curves in Figure 20 could be based on a component level abstraction. Yet, the decision-maker desires the knowledge of the uncertainty associated with the entire system, or aircraft. To apply the method of analogy of the reducing uncertainty as the

technology progresses, one must consider the uncertainty of the technology at the component level concurrently with the uncertainty of the entire system, and thus, the impact of the technology to the entire system. From this level of abstraction, the method of analogy applies and the entire system uncertainty reduces as the program progresses and is the result of all contributing component uncertainties as depicted in Figure 21. In a recent Science Applications International Corporation (SAIC) report to NASA [95], the original NASA TRL definitions were modified as listed in Table VI. As is evident, the “component” aspect was de-emphasized and the TRLs may be assumed to be at a system level of abstraction.

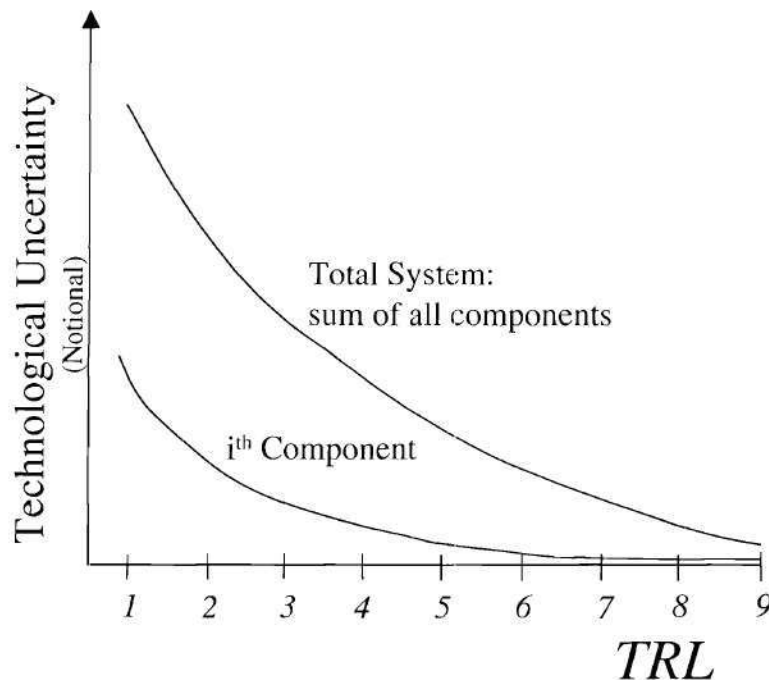


Figure 21: Technological Uncertainty

Table VI: SAIC Modified TRL Descriptions

Description	Level	Qualifier or Development Hurdle
Basic Research	1	Basic scientific/engineering principles observed and reported
Feasibility Research	2	Technology concept, application, and potential benefits formulated (candidate system selected)
Feasibility Research	3	Analytic and/or experimental proof-of-concept completed (proof of critical function or characteristic)
Technology Development	4	System concept observed in laboratory environment (breadboard test)
Technology Development	5	System concept tested and potential benefits substantiated in a controlled relevant environment
System Development	6	Prototype of system concept is demonstrated in a relevant environment
System Development	7	System prototype is tested and potential benefits substantiated more broadly in a relevant environment
Operational Verification	8	Actual system constructed and demonstrated, and benefits substantiated in a relevant environment
Operational Verification	9	Operational use of actual system tested, and benefits proven

Technology Forecasting

The next step is to identify forecasting techniques to bound, quantify, and estimate the technological uncertainty at the system level. The primary purpose of forecasting, in any context, is to provide the decision-maker with adequate information on which future decisions, company strategies, and business cases may be based. Two broad categories of forecasting exist: exploratory and normative. Exploratory forecasting techniques consider historical trends and extrapolate into the future to predict what may happen. "The feasibility of this process depends upon an assumption that progress is evolutionary and does follow a regular pattern." [37] The normative method begins with future goals and

works backward to identify the levels of performance needed to obtain the desired goals, if at all achievable with the resources available. This approach is equivalent to the Technology Impact Forecasting (TIF) environment that establishes how much improvement is needed from the various disciplines to achieve future customer requirements [41,59,74] as discussed with the avenues for infusing new technologies at the end of Step 5. Thus, TIF may be classified as a normative forecasting technique and TIES as an exploratory forecasting technique.

Either normative or exploratory utilizes one, or combinations, of four traditional forecasting techniques: S-curves, trend extrapolation, Delphi method, or scenario development [96]. The first two techniques assume a functional form of a previous or existing technological growth pattern and extrapolate to a future time. Again, sufficient information must exist for the forecast to be accurate and of value to the decision-maker. If insufficient information exists, the Delphi method is a structured means of incorporating expert opinions (usually subjective) through questionnaires and controlled feedback to estimate a technology impact and the confidence of achieving that impact. Based on numerous development programs identified by Martino [27] and Porter [94], the uncertainty should diminish if the program is successful in achieving the desired goals as depicted in Figure 21. Finally, the scenario development assumes some future status of the world (economic, political, etc.) and its influence on the technology progress to shape the development curve [37,94] and usually disrupts the technology progress at a pre-specified time.

If sufficient program monitoring is performed in the early phases of a development, a technology impact trend may be established and the first two techniques utilized. This trend may then be forecasted to a future time (or a TRL) and the impact quantified as a function of time, or program schedule. Yet, if a technology is in the infancy stages and little information is available as to the detailed progress, insufficient information exists to forecast the technology or estimate the uncertainty and the Delphi method must be used. The irony exists that a considerable quantity of data is required to sufficiently forecast, but the need for forecasting is more prominent when insufficient information exists, as in the conceptual phases of aircraft design.

Bounding Technological Uncertainty

If a technology is in the infancy stage of development (low TRL), the shape of the development curve is not easy to predict, due to lack of substantial data to establish a trend. Hence, the forecast must rely on expert, subjective opinions through the Delphi method with an assumed growth pattern. Subsequently, the forecast should focus on the evaluation of “the potential commercial benefits [and penalties] that might be achieved IF the [program] is successful” [37] and can be matured to the point of full-scale application (i.e., TRL=9). As more information and data becomes available, the forecast should be updated and re-evaluated.

Based on this rationale, the uncertainty, or confidence limits, may be bound based on a logical reasoning and with the method of analogy to *what should* happen as a technology program progresses without any unforeseen problems. For example, one may assume that a successful technology program develops along a linear trend as shown in Figure 22. Point “A” represents a technology in the infancy stage of development,

TRL=2. The desired capability of the performance improvement is Point “D” and is assumed to be the expert defined impact when a TRL of 9 is reached. This point is not yet fully realized due to knowledge impediments, and may actually be higher or lower than the expert defined limit when the technology reaches a TRL of 9. Points “B”, TRL=5, and “C”, TRL=8, represent other levels of technology maturation.

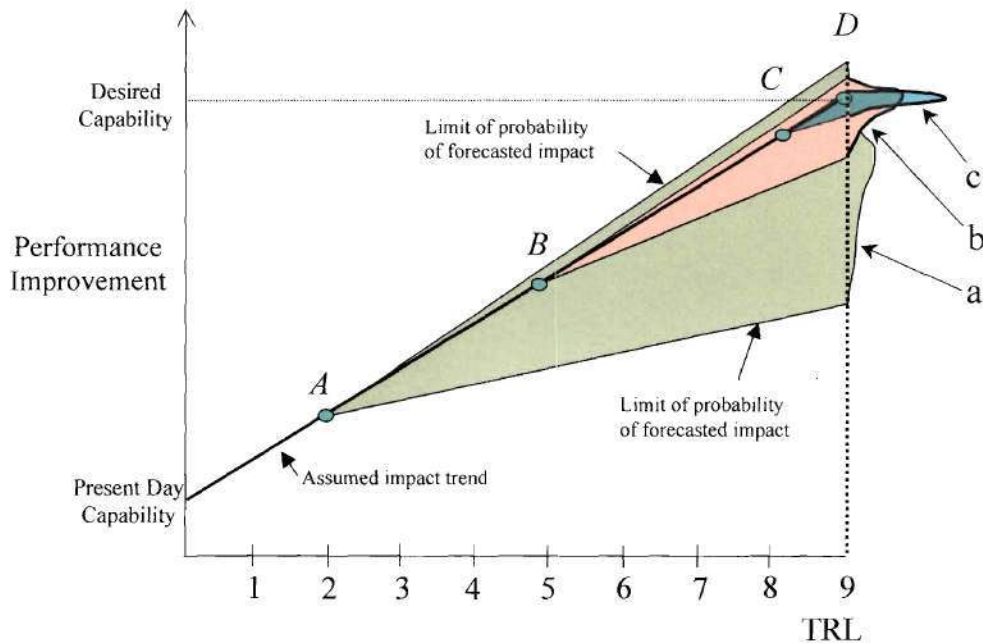


Figure 22: Uncertainty in Forecasting a Technology

To place bounds on the uncertainty of the technology, one must realize the two additive sources of uncertainty. First, the inherent uncertainty associated with the technology development as described previously. Second, there is uncertainty associated with forecasting the trend. Specifically, the confidence limits of achieving a desired value “broaden as the time frame of the forecast increases, reflecting the growing level of uncertainty”[97] in knowledge. A tangible analogy of this type of uncertainty is forecasting the price of fuel. One could forecast (or estimate) what the fuel price would

be tomorrow with a very high confidence, say \$1.39 per gallon \pm \$0.01 where fuel is \$1.39 per gallon today. However, the confidence of what the price will be in fifty years is very low and uncertainty is very high, say \$2.97 per gallon " \pm \$?". If one applies this analogy to forecast an immature technology to a future time (i.e. TRL), the confidence limits should spread. Consider Point "A", since the time frame of the forecast to the desired impact value is large, the distribution is very wide as shown by distribution "a". Yet, for a high TRL value, the confidence of achieving the desired technology improvement increases since the forecast is for a shorter time frame and more information is available regarding the technology as shown by distribution "c".

As shown in Figure 22 for the distributions ("a", "b", and "c"), the uncertainty in achieving the desired improvement is not necessarily normally distributed and the mode value should deviate, where the mode value is defined as the point of largest frequency. In fact, the distribution should be skewed towards the desired level if the expert opinion is relatively accurate. Based on this rationale, shape distributions associated with different TRLs may be established and can be based on qualitative reasoning, assuming insufficient data is available for the technologies considered. However, the distribution definitions should be modified, as more program tracking information becomes available.

Step 6 Summary:

Inputs: Morphological Matrix, probability of success values for each metric

Techniques: method of analogy, literature reviews, IPTs, expert questionnaires

Outputs: applicable technologies identified with associated TRL, TCM, and TIM

Step 7: Technology Evaluation

In this step, the technologies identified in Step 6 are applied to the vehicle concept and evaluated. The evaluation provides data and information to the decision-maker whereby selection of the proper mix of technologies is performed in Step 8. Yet, generating the data needed to conduct the search is dominated by the *curse of dimensionality*. Depending upon the number of technologies (n) considered, the combinatorial problem could be enormous. If all combinations are physically compatible and assuming only an “on” or “off” condition, then 2^n combinations would exist. In addition, the technology “k” factor vector that influences a vehicle is probabilistic and a CDF must be generated for each combination, hence, the *curse of uncertainty*. If the computational expense of the analysis is acceptable, a full-factorial investigation could ensue. Yet, if the computational expense is too high (e.g., a finite element analysis), an alternate evaluation method is needed. One potential method is a genetic algorithm formulation. Gen defines genetic algorithms as “a class of general-purpose search methods...which can make a remarkable balance between exploration and exploitation of the search [of the design or technology] space” to find the best family of alternatives [98].

For the purposes of this research, the computational expense is manageable due to the means by which the technology “k” vectors are modeled with the aid of a metamodel representation. Consider the TIM in Figure 19 and a metamodel representation of a system metric. If one were to bind each “k” factor element of the technical vector, a metamodel in the form of a second-order Response Surface Equation (RSE), Equation (4), could be generated for each of the system metrics for ‘n’ “k” factors [93].

$$R = b_o + \sum_{i=1}^n b_i k_i + \sum_{i=1}^n b_{ii} k_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^n b_{ij} k_i k_j \quad (4)$$

The independent variable ranges, k_i , are defined from the TIM. A summation of all the “+” values in a given row defines the upper limit and summing all of the “-” defines the lower limit. For example from Figure 19, “k” factor 1, k_1 , varies between -10% and +4%, while “k” factor 4, k_4 , between -4% and +3%. Hence, the system metrics can be defined as a function of “k” factors for a fixed geometry using Equation 4. An RSE of this form is defined for each system metric and is valid for the defined “k” factor ranges. The impact of a technology on a system metric can be evaluated via a simple calculation of Equation 4 with the appropriate technology “k” vector values or distributions. To create the metric RSEs, the M&S environment is needed, as was the case with the design space investigation.

The evaluation of the technologies considered for infusion can be performed from two perspectives, depending on the level of knowledge, information desired, stage of the design, and at what level of abstraction is desired. The two perspectives are either deterministic or probabilistic.

Deterministic Evaluation

The motivation for a deterministic evaluation is two-fold. In many cases, a plethora of technologies need to be considered and the decision-maker wishes to downsize the problem with a rapid assessment. Second, the decision-maker has very little knowledge of the technology due to a high immaturity (a TRL of 1 or 2) and a quick assessment is desired. The results from the latter point are the “best” and “worst” case scenarios since

the inclusion of uncertainty will only degrade the impact. In essence, the technology impact thresholds are established.

Evaluation of a Single Technology

The impact of a single technology can be evaluated via a calculation of the RSEs with the appropriate technology “k” vector values from the TIM. Take for example a case where an RSE has been generated for 3 “k” factors (k_1 =total drag, k_2 =SFC, k_3 =O&S). If the impact of technology T1 was to reduce drag by 10% ($k_{1,T1} = -10\%$), increase O&S by 3% ($k_{3,T1} = +3\%$), and had no impact on SFC ($k_{2,T1} = 0\%$), the RSE would become

$$R_{|T1} = b_o + \left(\sum_{i=1}^3 b_i k_i + \sum_{i=1}^3 b_{ii} k_i^2 + \sum_{i=1}^2 \sum_{j=i+1}^3 b_{ij} k_i k_j \right)_{T1} \quad (5)$$

$$R_{|T1} = b_o + \left(b_1 k_1 + b_2 k_2 + b_3 k_3 + b_{11} k_1^2 + b_{22} k_2^2 + b_{33} k_3^2 + b_{12} k_1 k_2 + b_{13} k_1 k_3 + b_{23} k_2 k_3 \right)_{T1} \quad (6)$$

but, $k_{1,T1} = -10\%$, $k_{2,T1} = 0\%$, and $k_{3,T1} = +3\%$, such that

$$R_{|T1} = b_o + b_1(-10\%) + b_3(+3\%) + b_{11}(-10\%)^2 + b_{33}(+3\%)^2 + b_{13}(-10\%)(+3\%) \quad (7)$$

This procedure is repeated for as many technologies and metrics that are considered. Recall that the coefficient terms were determined via the least squares analysis of the DoE.

Evaluation of Multiple Technologies

The evaluation of a combination of technologies assumes that the impacts of the individual technologies are additive. The additive nature is assumed as a valid approach since the technology impacts are modeled at a disciplinary level and the interactions between technologies will be captured. Although other techniques could be used to evaluate the impact of multiple technologies, an additive approach was straightforward.

Moreover, the interactions amongst different technologies are captured through the simple summation of the “k” factors. At present, no technology combination can be employed that violates this assumption. This assumption is best explained through example. Consider the RSE example for the single technology case described above. Let T1 and T2 be defined as in Equation 8. Assuming the technologies are additive implies that the impact on a metric due to T1+T2 is the summation of the individual “k” factors and Equation 9 is obtained. The same procedure performed to calculate the single technology is applicable for the new technology vector in Equation 9. The method of calculation may be repeated for all compatible combinations.

$$T1 = f \left\{ \begin{array}{l} k_{1,T1} = k_{drag} = -10\% \\ k_{2,T1} = k_{SFC} = 0\% \\ k_{3,T1} = k_{O\&S} = +3\% \end{array} \right\}, T2 = f \left\{ \begin{array}{l} k_{1,T2} = k_{drag} = +3\% \\ k_{2,T2} = k_{SFC} = +5\% \\ k_{3,T2} = k_{O\&S} = -5\% \end{array} \right\} \quad (8)$$

$$R_{T1+T2} = f \left\{ \begin{array}{l} k_{1,T1} + k_{1,T2} \\ k_{2,T1} + k_{2,T2} \\ k_{3,T1} + k_{3,T2} \end{array} \right\} = f \left\{ \begin{array}{l} k_{1,T1+T2} = -10\% + 3\% \\ k_{2,T1+T2} = 0\% + 5\% \\ k_{3,T1+T2} = +3\% - 5\% \end{array} \right\} = f \left\{ \begin{array}{l} k_{1,T1+T2} = -7\% \\ k_{2,T1+T2} = 5\% \\ k_{3,T1+T2} = -2\% \end{array} \right\} \quad (9)$$

Technology Sensitivities

The decision-maker may desire insight to the sensitivity of the metrics to the technologies. This can be accomplished with a full-factorial evaluation of the technologies. A full factorial procedure based on 2 levels - “on” and “off”, constitutes 2^n evaluations for “n” technologies, as shown in Figure 23. The JMP[®] statistical program may be used to visualize the sensitivities via the Prediction Profiler feature. An example is shown in Figure 24. The decision-maker can readily identify the technologies that most significantly impacted the system metrics. In this example, T4 provided a significant reduction in the economic metric, while T3 increased it. The profiler provides a rapid,

visual environment that the decision-maker may perform trade-offs. Caution should be exercised since the compatibility rules are not inherent in the sensitivities, and care should be taken prior to arbitrarily turning “on” a mix of technologies.

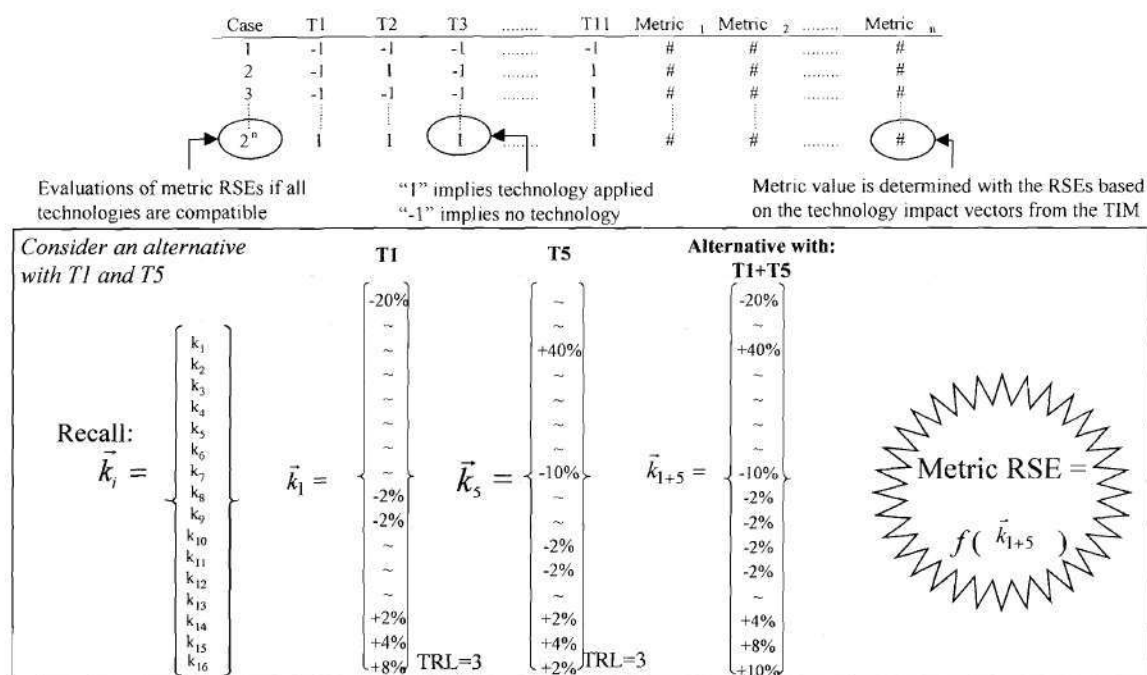


Figure 23: Deterministic Full-Factorial Technology Evaluation

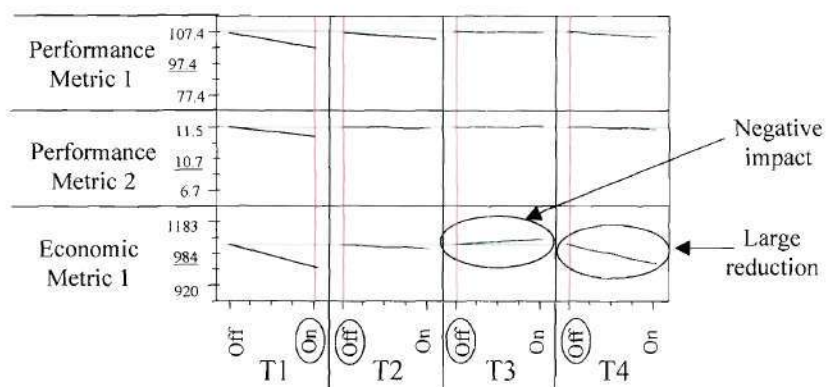


Figure 24: Full Factorial Deterministic Technology Sensitivities

Probabilistic Evaluation

The motivation for a probabilistic evaluation is to provide a more realistic assessment of the uncertainty and risk associated with the impact of immature technologies. Probabilistically evaluating a single technology or a combination of technologies is similar to the deterministic evaluation, except that the “k” factors are distributions rather than single point values. To quantify the impact on a system metric, a Monte Carlo Simulation (MCS) is performed with user defined frequency distributions *for each “k” factor element* and a CDF obtained for each system metric. If one assumes that the technologies are additive, then a combination of two or more technologies remains a simple MCS on the RSE. Now, instead of the response, R, being a function of only one “k” vector (i.e., technology), it is a function of the sum of the combination of vectors (i.e., sum of technologies). For example, if one wants to determine a system metric value due to a combination of T1 and T2, distributions are assigned to *each element of both technology “k” vectors*. Subsequently, a random number generator selects a value for the first element of the T1 vector and the first element from the T2 vector, based on the user-defined frequency distributions. Then, the two values are added to obtain a “new” first element that is inserted into RSE and the system metric value calculated. This is done for each element and each time a new combination of technologies is desired. This process is automated with the software package Crystal Ball[®] [99], which is a Microsoft EXCEL[®] “add-in” function.

The procedure to probabilistically evaluate technology combinations is:

1. Define distributions associated with technology's TRL
2. Run a random number generator for each element of the technology vector
3. Add elements of the technology vectors that are "on"
4. Insert values of the new vector element into the RSE and recalculate
5. Repeat for as many MCS runs desired
6. Extract metric data (CDF or PDF)
7. Repeat steps 1-6 for each technology combination

How do the results from a probabilistic evaluation differ from the deterministic?

The answer is best described from a visual representation as in Figure 25. From the deterministic assessment, the response is a point value, depicted as R_i , and may be defined as the "theoretical" impact of a technology combination. When uncertainty is introduced, the response becomes uncertain as shown by the PDF and is defined by a mean and a variance. Based on the rationale of an immature technology discussed previously, if a technology is not fully matured, i.e., $TRL < 9$, then the performance improvement value anticipated from the technology is not fully realized. This is evident by the mean value of the response, μR_i , being shifted from the value where no uncertainty is included, R_i . Thus, there is degradation, $\Delta \mu R_i$, in the response from the inclusion of uncertainty.

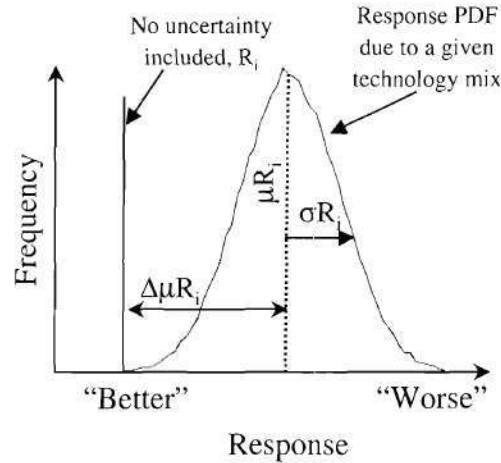


Figure 25: Impact of Technological Uncertainty on a Response

The technology sensitivities may be established in the same manner as was performed in the deterministic evaluation, but for a given response, additional information must be extracted; the “certain” value, R_i , the change in the mean value, $\Delta\mu R_i$, and the standard deviation, σR_i . Hence, the impact of technology, T_j , on a given response, R_i , can be defined as a normal distribution as in Equation 10. The specific relationship between the response variability and TRL is explored in Chapter IV.

$$R_i(\mu, \sigma)|_{T_j} = (R_{ij} + \Delta\mu R_{ij}, \sigma R_{ij}) \quad (10)$$

An example metric sensitivity is depicted in Figure 26. The profiler is interpreted in the same manner discussed previously. For example, adding T2 to the vehicle results in a reduction of a performance metric, R_i , say gross weight. Yet, the technology is at a TRL of 3 and the $\Delta\mu$ of the performance metric is large (gross weight increases), which implies that the expected value of performance, when technological uncertainty is factored in, will not be as substantial as the “certain” value reduction. The “certain” value in this case would be the technology impact threshold, the “best” that could ever be

achieved. Further, the standard deviation, or measure of distribution spread, of the performance due to T2 is large. On the other hand, T1 does not affect either metric, as shown by the flat lines for the prediction traces. One should not dismiss T1 in this case, but should investigate if the true nature of the technology impact is being modeled. For example, if T1 were a technology that improved the handling qualities of the system and the handling qualities were not being quantitatively evaluated, no positive influence would be evident. Hence, one should take care before arbitrarily dismissing a technology.

Finally, if the decision-maker desires a minimum impact level of a technology, the probability of meeting that target is established by placing the target value on the metric CDF and reading the corresponding probability level. This approach is similar to the system feasibility evaluation in Step 5. Or, if technological risk is of interest, then the allowable probability (or risk) will indicate the technology impact as read from the CDF.

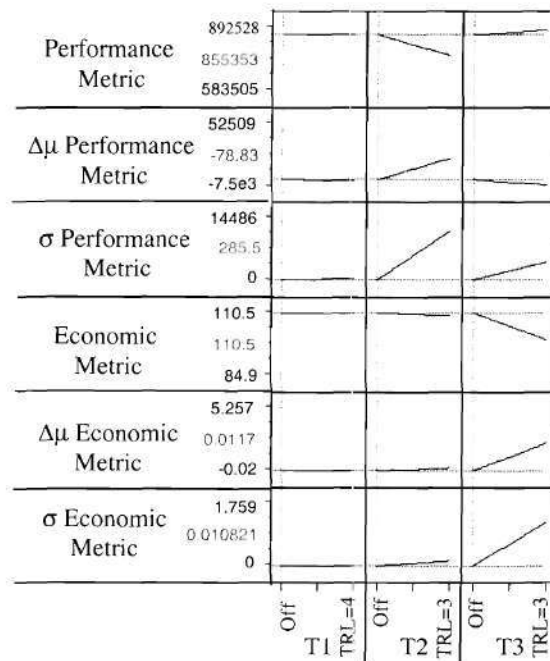


Figure 26: Example Probabilistic Technology Sensitivity

Population of Decision Matrix

Prior to selecting the best mix of technologies, a Decision Matrix (DM) must be created. The alternative concepts, i.e., different technology combinations, identified in Step 6 form the rows and the system metrics from the problem definition in Step 1 form the columns as shown in Figure 27. The deterministic elements of the matrix are populated from the results obtained in Step 7 for each alternative and metric. Since the metrics are in the form of CDFs, the decision maker has the ability to select a confidence level associated with a given metric. *The confidence level is also related to the risk or uncertainty associated with a particular technology and the level selection is purely subjective.* The corresponding value of the metric, at a fixed confidence level, is inserted into the appropriate cell of the matrix. This process is repeated for each metric and each compatible technology concept until the DM is fully populated. Further, a DM is created for each confidence level of interest.

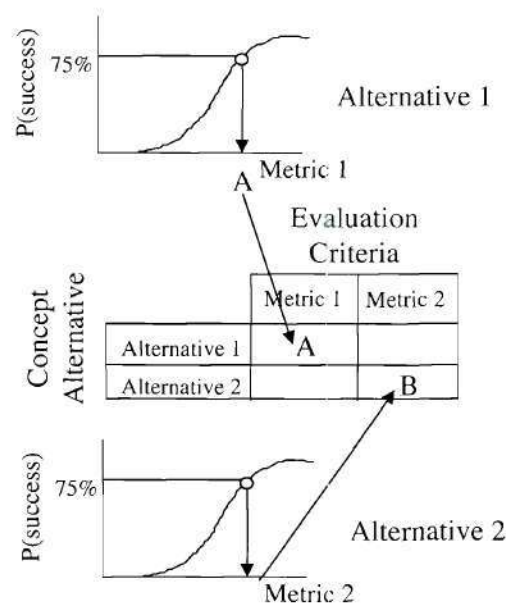


Figure 27: Populating the Decision Matrix

Step 7 Summary:

Inputs: Technology Readiness Level, Technology Impact Matrix, Technology Compatibility Matrix

Techniques: Response Surface Methodology and Monte Carlo Simulation

Outputs: impact of technology combinations, “theoretical” impacts, uncertain impacts (CDF or PDF), prediction profiler, decision matrix

Step 8: Technology Selection

For any multiple attribute, constraint, or criteria problem, the selection of the “best” family of alternatives is inherently subjective with no single answer fulfilling all requirements. Three techniques are proposed for the TIES method to account for the subjectivity of the problem and include:

- 1) Multi-Attribute Decision-Making techniques
- 2) Technology Frontiers
- 3) Resource Allocation

Multi-Attribute Decision-Making (MADM) techniques

One particular MADM technique that is very simple and easy to implement is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [46]. TOPSIS is based on the notion that the best alternative amongst a finite set should have the shortest Euclidean distance to the ideal solution and farthest from the negative-ideal solution. TOPSIS provides a preference order of the deterministic values contained in the DM, at a given confidence level, resulting in a ranking of the best alternative concepts

and is the most appropriate MADM technique based on the selection process outlined in Chapter II.

The TOPSIS technique begins with the DM created in Step 7 for “n” criteria and “m” alternatives in Equation 11, where Alt_i is the i^{th} alternative, R_j is the j^{th} criteria and r_{ij} is the numerical outcome of the i^{th} alternative with respect to the j^{th} criterion. TOPSIS is executed in six steps as described by Hwang [46].

$$DM = \begin{matrix} & R_1 & \cdots & R_j & \cdots & R_n \\ \begin{matrix} Alt_1 \\ \vdots \\ Alt_i \\ \vdots \\ Alt_m \end{matrix} & \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \end{matrix} \quad (11)$$

Step 1: Construct the normalized DM: This step normalizes each criterion to allow for an “apples-to-apples” comparison. Each criterion is divided by the Euclidean norm of the total outcome vector of the given criterion, such that each criterion vector has the same unit length as in Equation 12.

$$x_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^m r_{ij}^2}} \quad (12)$$

Step 2: Construct the weighted normalized DM: The subjectivity of the selection process is introduced through weights on each criterion based on the preference of the decision-maker, $\bar{w} = (w_1, w_2, \dots, w_j, \dots, w_n)$, $\sum_{j=1}^n w_j = 1$. The normalized DM is calculated by multiplying each column of the matrix X_j with its associated weight, w_j . Thus, the weighted normalized DM, V , is equal to

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1j} & \cdots & v_{1n} \\ \vdots & & \vdots & & \vdots \\ v_{i1} & \cdots & v_{ij} & \cdots & v_{in} \\ \vdots & & \vdots & & \vdots \\ v_{m1} & \cdots & v_{mj} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 x_{11} & \cdots & w_j x_{1j} & \cdots & w_n x_{1n} \\ \vdots & & \vdots & & \vdots \\ w_1 x_{i1} & \cdots & w_j x_{ij} & \cdots & w_n x_{in} \\ \vdots & & \vdots & & \vdots \\ w_1 x_{m1} & \cdots & w_j x_{mj} & \cdots & w_n x_{mn} \end{bmatrix} \quad (13)$$

Step 3: Determine ideal and negative ideal solutions: Let two artificial alternatives, A^* and A^- , be defined as

$$A^* = \left\{ \left(\max_i v_{ij} \mid j \in J \right), \left(\min_i v_{ij} \mid j \in J' \right), i = 1, 2, \dots, m \right\} \quad (14)$$

$$= \{v_1^*, v_2^*, \dots, v_j^*, \dots, v_n^*\}$$

$$A^- = \left\{ \left(\min_i v_{ij} \mid j \in J \right), \left(\max_i v_{ij} \mid j \in J' \right), i = 1, 2, \dots, m \right\} \quad (15)$$

$$= \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\}$$

where

$$J = \{j = 1, 2, \dots, n \mid j \text{ associated with a benefit criteria}\}$$

$$J' = \{j = 1, 2, \dots, n \mid j \text{ associated with a cost criteria}\}$$

“Benefit” is an attribute for which maximization is desired and “cost” is an attribute for which minimization is desired. Thus, the two artificial alternatives, A^* and A^- , indicate the most preferable alternative (positive ideal solution) and the least preferable alternative (negative ideal solution), respectively. The most preferable solution is nothing more than a hypothetical vector of the “best” feature of each metric, but is not a realizable solution, while the least preferable is the complement vector.

Step 4: Calculate the separation measure: The n-dimensional Euclidean distance calculates the separation, or distance, between each alternative. The separation of each alternative from the positive ideal solution is given by

$$S_{i+} = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^*)^2}, \quad i = 1, 2, \dots, m \quad (16)$$

And, the separation from the negative ideal solution is given by

$$S_{i-} = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, \quad i = 1, 2, \dots, m \quad (17)$$

Step 5: Calculate the relative closeness to ideal solution: The relative closeness of each alternative, Alt_i , with respect to A^* is defined in Equation 18. If $C_{i+} = 1$, $Alt_i = A^*$ and if $C_{i+} = 0$, $Alt_i = A^-$. An alternative is closest to A^* as C_{i+} approaches 1.

$$C_{i+} = \frac{S_{i-}}{S_{i+} + S_{i-}}, \quad 0 < C_{i+} < 1, \quad i = 1, 2, \dots, m \quad (18)$$

Step 6: Rank the preference order: The ranking of the best alternatives may be determined from a ranking in descending order of C_{i+} .

There are two limitations to TOPSIS and MADM techniques in general. First, TOPSIS requires deterministic values when ranking the alternatives, yet, the technology impacts on the system are probabilistic. Thus, information regarding the different metric CDFs may be lost in the down select process and include the variability that is associated with a given mix of technologies. As a simplified solution the limitations, one could select the top alternatives for different confidence levels and weighting scenarios.

Once the top alternatives are determined, the results may be compared to conclude if any combinations consistently rank in the top ten or so, regardless of confidence level. Although this is a simple approach, visualizing the impact of uncertainty of the top alternatives is not necessarily intuitive. One should note that the results of the top alternatives for different confidence levels might not be identical due to the fact that the

distribution variance for each technology alternative changes. The variance is driven by the uncertainty associated with an immature technology (low TRL) and *increases when more technologies are added*. Finally, the numerical values obtained from the ranking of alternatives are not intuitive to the decision-maker, especially for visual representations as discussed in Chapter II. Thus, additional selection techniques are suggested to aid in the decision-making process.

Technology Frontiers

The inefficiencies of the MADM techniques, deterministic, and non-intuitive numerical results may be improved with the use of Technology Frontiers. Technology Frontiers are defined as the limiting threshold of an “effectiveness” parameter, whereby uncertainty is captured and more tangible results presented. The technology frontier takes a similar approach as TOPSIS. An Effectiveness Parameter (EP) is a user-defined function for which maximization is desired. As in the case of TOPSIS, preference of the different criteria is introduced through weighting factors. Two intuitive parameters may be defined as Performance Effectiveness (PE) and Economics Effectiveness (EE). Similar to the “benefit” and “cost” criteria used in TOPSIS, “benefit” and “cost” performance and economic effectiveness parameters are defined, such that:

$$PE^* = \frac{PE}{PE_{Baseline}} \quad (19)$$

$$PE^- = \frac{PE_{Baseline}}{PE} \quad (20)$$

$$EE^* = \frac{EE}{EE_{Baseline}} \quad (21)$$

$$EE^- = \frac{EE_{Baseline}}{EE} \quad (22)$$

where PE^* and EE^* are “benefit” parameters and PE^- and EE^- are “cost” parameters. Examples of performance parameters include weight, range, speed, etc., while economic parameters include acquisition price, ROI, and so on. $PE_{baseline}$ and $EE_{baseline}$ correspond to datum points for normalization and are at the decision-maker’s discretion. Creating a PE and an EE for each confidence level of interest captures the uncertainty of the responses and the influence of uncertainty will become clear momentarily. Next, subjectivity is introduced through weights on each criterion based on the decision-maker’s preference.

$$\begin{aligned}\bar{w}_{PE^*} &= (w_{1, PE^*}, w_{2, PE^*}, \dots, w_{j, PE^*}, \dots, w_{n, PE^*}) \\ \bar{w}_{PE^-} &= (w_{1, PE^-}, w_{2, PE^-}, \dots, w_{j, PE^-}, \dots, w_{n', PE^-}) \\ \sum_{j=1}^n w_{j, PE^*} + \sum_{j=1}^{n'} w_{j, PE^-} &= 1 \\ n + n' &= N\end{aligned}\quad (23)$$

$$\begin{aligned}\bar{w}_{EE^*} &= (w_{1, EE^*}, w_{2, EE^*}, \dots, w_{j, EE^*}, \dots, w_{m, EE^*}) \\ \bar{w}_{EE^-} &= (w_{1, EE^-}, w_{2, EE^-}, \dots, w_{j, EE^-}, \dots, w_{m', EE^-}) \\ \sum_{j=1}^m w_{j, EE^*} + \sum_{j=1}^{m'} w_{j, EE^-} &= 1 \\ m + m' &= M\end{aligned}\quad (24)$$

where “N” is the number of performance criteria and “M” is the number of economic criteria. Thus, the PE and EE for a given alternative, Alt_i , are defined in Equations 25 and 26. The System Effectiveness for a given alternative, SE_{Alt_i} , is a summation of the PE_{Alt_i} and the EE_{Alt_i} with subjective weights placed on each parameter as in Equation 27.

$$PE_{Alt_i} = \sum_{j=1}^n w_{j, PE^*} PE_i^* + \sum_{j=1}^{n'} w_{j, PE^-} PE_i^- \quad (25)$$

$$EE_{Alt_i} = \sum_{j=1}^m w_{j, EE^*} EE_i^* + \sum_{j=1}^{m'} w_{j, EE^-} EE_i^- \quad (26)$$

$$SE_{Alt_i} = w_{perf} PE_{Alt_i} + (1 - w_{perf}) EE_{Alt_i} \quad (27)$$

Once the EPs are determined for each alternative, the technology space may be compared to any parameter of interest. One parameter of particular importance would be the investment costs associated with developing a technology combination to maturity, as depicted in Figure 28. This approach is similar to the notion of “system cost effectiveness” proposed by Mavris [29], which is the ratio of the benefit to the system relative to the cost of achieving those benefits. A similar approach to TOPSIS can be used to define the ideal solution for the technology space. A “best compromise” solution may be established based on the technology alternative that is closest to the ideal solution. The “best compromise” solution is similar to a Pareto optimal solution which implies that one metric cannot be improved any further without degrading another metric [100]. Finally, the Technology Frontier is established by placing a threshold curve around all of the technology alternatives and is analogous to a Pareto front [101]. The frontier implies that no alternative falls outside of the established boundary.

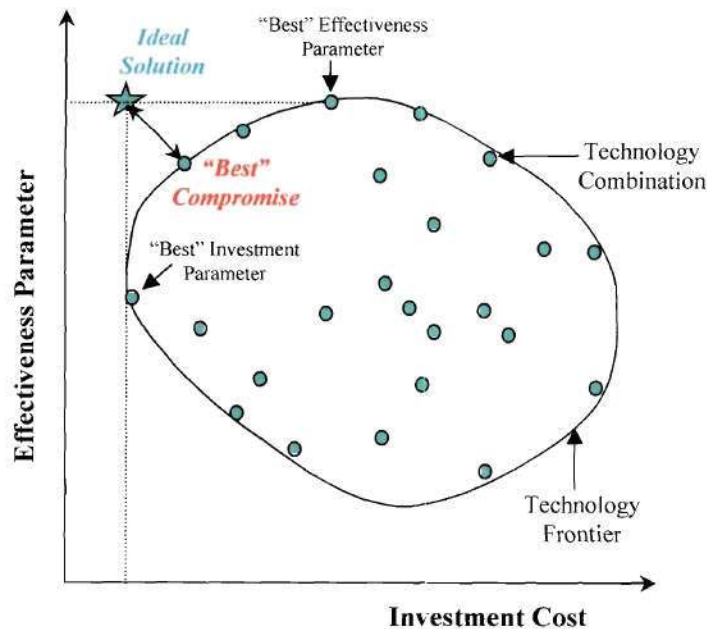


Figure 28: Example Technology Frontier

How will the Technology Frontier change for different levels of confidence? As discussed in Step 7 (Technology Evaluation), assessing a technology combination without uncertainty yields the theoretical limit of the technology impact. In this example, the theoretical limit corresponds to a confidence of 0% as shown on the right of Figure 29. If the EP is determined for each technology alternative based on this point, then the “theoretical” technology frontier is defined. Similarly, different frontiers may be established for different confidence levels. As a result, the technology frontiers for increasing confidence levels may tighten and produce a smaller technology space as shown on the left. The exact shape of these frontiers is to be determined through application in Chapter IV. Further, the “ideal” solution also shifts and reduces the EP magnitude while increasing the investment costs.

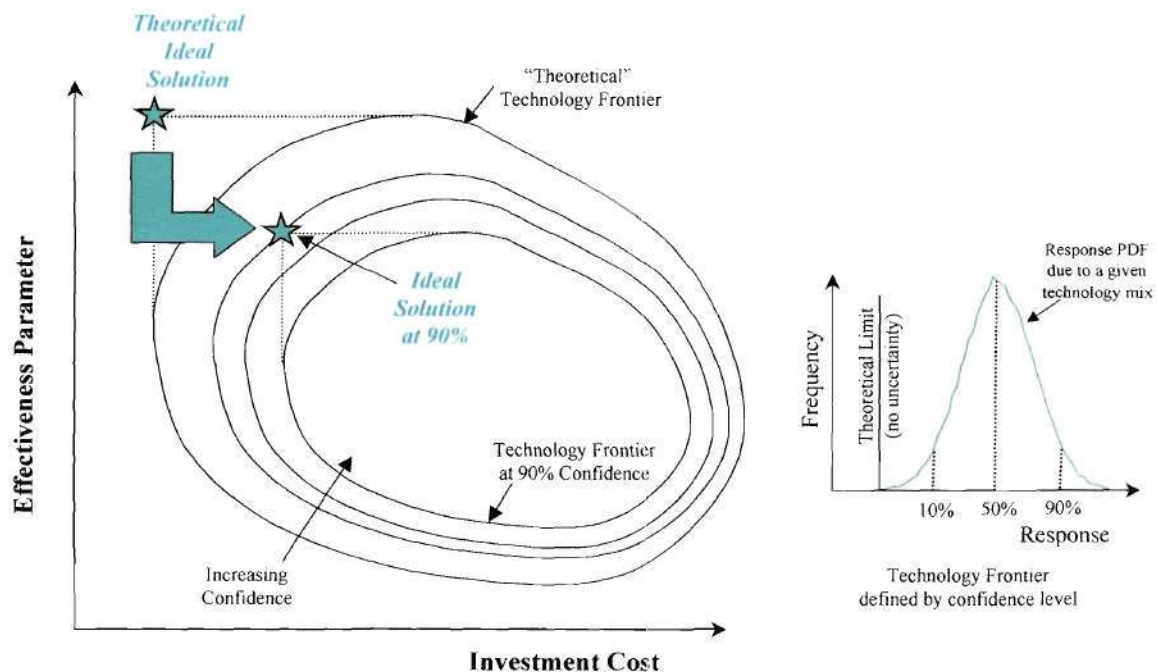


Figure 29: Example Probabilistic Technology Frontier

To identify the technology alternatives that may satisfy the customer requirements, or criteria, effectiveness thresholds should be established. An effectiveness threshold defines how much improvement is needed from each criterion to create a feasible space. A simplified means by which thresholds can be defined are based on the original PE and EE definitions, and the constrained metric target values, such that

$$PE_{\text{limit}}^* = \frac{PE_{\text{Target}}}{PE_{\text{Baseline}}} \quad (28)$$

$$PE_{\text{limit}}^- = \frac{PE_{\text{Baseline}}}{PE_{\text{Target}}} \quad (29)$$

$$EE_{\text{limit}}^* = \frac{EE_{\text{Target}}}{EE_{\text{Baseline}}} \quad (30)$$

$$EE_{\text{limit}}^- = \frac{EE_{\text{Baseline}}}{EE_{\text{Target}}} \quad (31)$$

If the baseline meets the constrained metric target value, the effectiveness parameter is set to one in order to avoid an artificial reduction of the threshold limit. The PE and EE thresholds become

$$PE_{\text{threshold}} = \sum_{j=1}^n w_{j, PE} PE_{\text{limit}}^* + \sum_{j=1}^{n'} w_{j, PE} PE_{\text{limit}}^- \quad (32)$$

$$EE_{\text{threshold}} = \sum_{j=1}^m w_{j, EE} EE_{\text{limit}}^* + \sum_{j=1}^{m'} w_{j, EE} EE_{\text{limit}}^- \quad (33)$$

and the threshold for the system effectiveness is

$$SE_{\text{threshold}} = w_{\text{perf}} PE_{\text{threshold}} + (1 - w_{\text{perf}}) EE_{\text{threshold}} \quad (34)$$

Once the thresholds are defined, the thresholds can be overlaid as a constraint on the technology frontier plots, as shown in Figure 30. A budget limit on the investment monies available should also be overlaid. The two threshold limits define the feasible technology space with respect to performance, economics, or the entire system. The

technology alternatives that fall within this region are easily identified and may be investigated in further detail. If no alternatives fall within this region, then no technology combinations can meet the imposed customer requirements. Yet, the combinations that come closest to the feasible region may be readily identified. For example, the combination of T3+T7+T9 in Figure 30 is very close to the feasible range and a slight reduction in investment expenditures will make this combination feasible. The decision-maker may re-evaluate the development schedule of the three technologies to determine if costs savings can be achieved. The technology frontiers provide a rapid and visual means of selecting a family of feasible alternatives while including technological uncertainty via multiple frontiers.

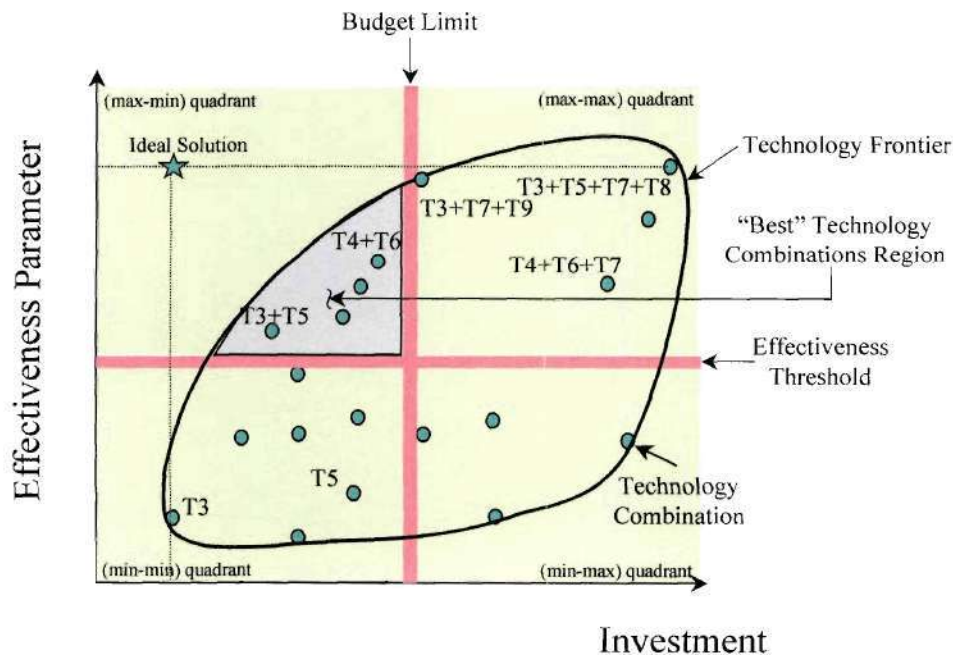


Figure 30: Identification of "Best" Technology Combination Region

Resource Allocation

MADM and technology frontier techniques to select the best technology combinations that satisfy a set of customer requirements are not the only means by which alternatives may be selected. The final approach is a quantitative resource allocation investigation. From the first two approaches, a family of alternatives are identified that may satisfy the customer requirements with an associated confidence. In general, the more technologies added, the better the performance of the system. Yet, it is highly unlikely that a company has the expendable Research and Development (R&D) budget and resources to develop more than a few technologies at a time. Thus, a decision-maker desires guidance as to which technology programs should be pursued so that scarce resources may be allocated in an optimal fashion. Unlike the traditional methods of resource allocation mentioned previously, the approach taken here is more rigorous and quantitative, such that investment decisions made regarding a particular technology development may be justified and tracked.

Froham summarizes that traditional R&D projects allocate resources based on past activity in the specific research area rather than the potential bottom line contributions and a justified business case. In addition, far-term thinking and planning is not generally the trend. Short-term funding tends to be the driver for allocating resources which leads to projects and endeavors that are not broader-range or do not have long-term or high payoffs for the particular company [85]. The approach herein attempts to deal with these shortcomings. The key aspect of this approach is that the “big hitter” technologies are rapidly and efficiently identified and provide quantitative justification of technology investment program decisions.

The execution of this approach is nothing more than a manipulation of data that was generated in previous steps. In particular, the data generated in Step 7 is reorganized into a more insightful form. This is performed with a comparison of the individual technology impacts to the conventional configuration for each metric. Consider the cost CDF for an arbitrary technology, T_i , shown in Figure 31. The decision-maker would select particular confidence levels and calculate the relative change of the alternative's value as compared to the baseline, resulting in a $\Delta\%$ cost from the baseline. This can be done for each metric and alternative for different confidence levels. In this example, T_4 provides the most significant reduction from the baseline. The 0% reduction represents the cost of the baseline vehicle or datum value.

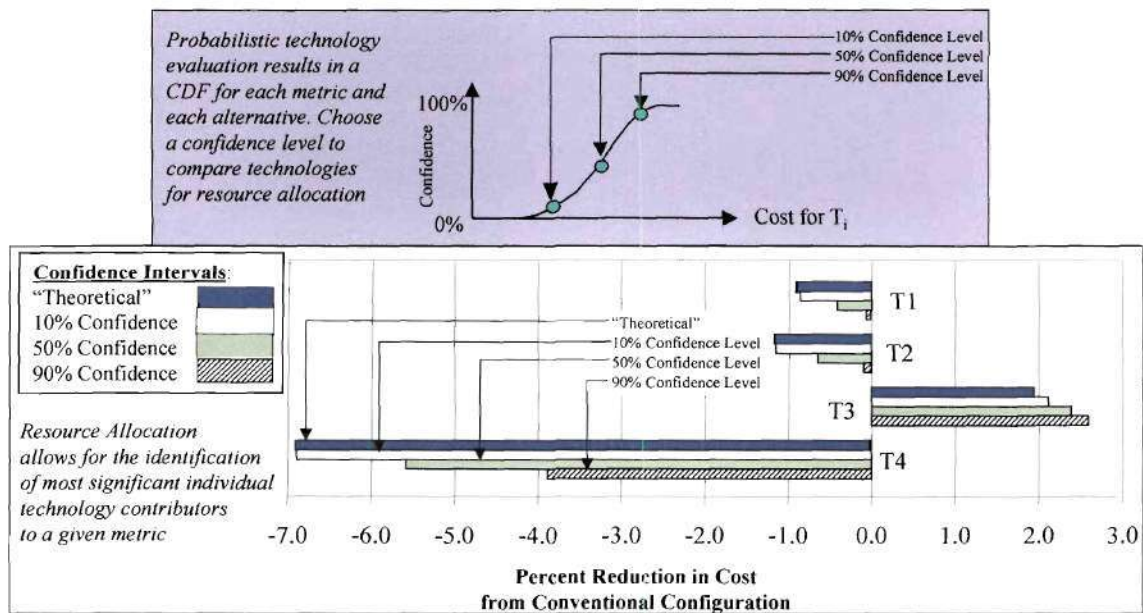


Figure 31: Technology Resource Allocation

However, what may be good for one metric will surely degrade another. For example, consider a performance and a cost metric in Figure 32, both metrics desire a minimum. For the performance metric, a target reduction needed from the conventional configuration to obtain a feasible concept is 7.5%, as shown by the vertical line. Both T3 and T6 provide the needed reduction with a confidence level of approximately 60%. Hence, either one of these technologies would be prime targets for increased R&D resources.

Yet, one must also consider the impact of a technology on the affordability and other performance metrics of the system. As shown in Figure 32, T3 and T6 increase the cost metric relative to the conventional configuration and could potentially hinder the success of the program. To the decision-maker, the further development of T3 should be in question, unless another technology was infused countering the negative economic impact. One example would be T2. This technology counters the negative impact of T3 by reducing both metrics, although it does not reduce performance as significantly as T3 or T6 in isolation. Also worth noting, with economic metrics, the “theoretical” limit does not necessarily correspond to the 0% or 100% confidence level as shown with T1, T3, and T6 in Figure 32. This process is repeated until a handful of technologies are deemed worthy for investment resources.

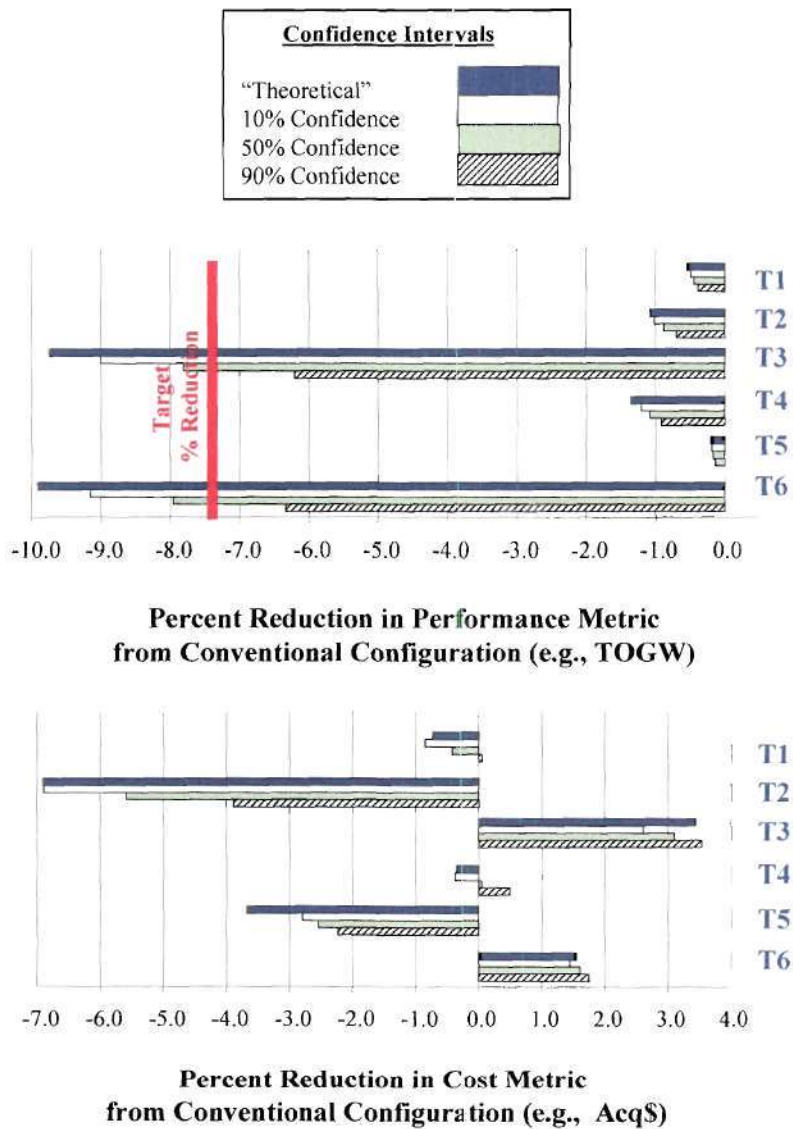


Figure 32: Comparison of Different Metrics for Resource Allocation

Step 8 Summary:

Inputs: decision matrices, subjective weightings

Techniques: MADM, technology frontiers, resource allocation

Outputs: best family of technology alternatives

A Final Solution?

The design of any complex, multi-attribute system is highly subjective, especially in the early phases of the development. Thus, the selection of a single concept alternative is highly dependent on the decision-maker's judgement and relative importance of the evaluation criteria. Because of this, the family of alternative concepts that have been identified through the execution of TIES should be carried through the design process to retain design freedom as long as possible. This process entails a re-investigation of the design space with the various technology alternatives that were deemed as the most significant from the selection step results. Subsequently, Steps 4 and 5 are repeated to determine if a different geometry will further increase the feasibility of the system for the family of technology alternatives. Thus, iteration is required within the TIES method. However, the iteration is rapid once the initial method is established.

Technology Identification, Evaluation, and Selection Method

This chapter has focused on the population of the inputs, techniques, and outputs needed to create a new design method that responds to the paradigm shift in the aerospace industry. Drawing on information presented for the execution of each step, the TIES method may be presented as shown in Figure 33. The techniques utilized to execute each step of the method were chosen based on robustness and generality and should allow for a substantial reduction in design cycle time and provide quantitative justification for design decisions.

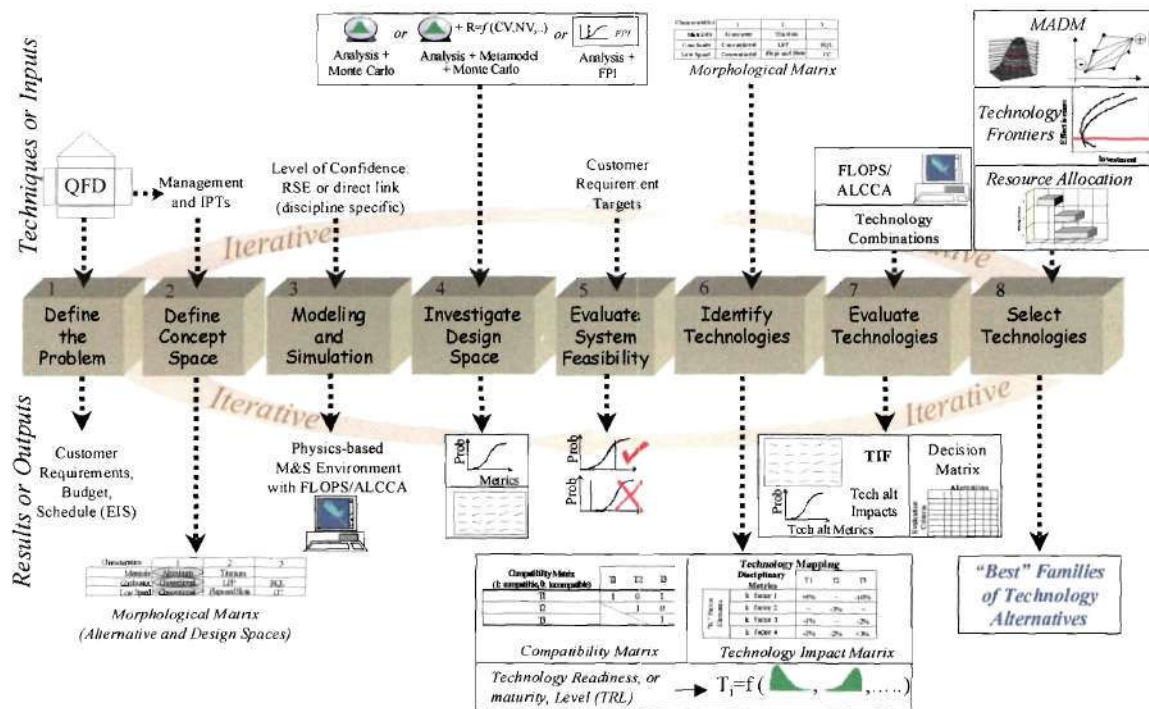


Figure 33: Technology Identification, Evaluation, and Selection Method

The potential applications of the TIES method are numerous. The steps required for implementation are generic such that any complex system could be analyzed. However, the basic requirements for application of TIES include the ability to identify a set of customer requirements for which the system may be judged as successful or not. Further, a Modeling and Simulation (M&S) environment in some capacity must exist whereby the customer requirements can be quantitatively assessed. Finally, the technologies to be infused to the system must be quantifiable in the M&S environment. The remaining steps are not specific to any class of systems or vehicles and the TIES method could be applied to a wide-range of complex systems including missiles, torpedoes, ships, power generators, automobiles, telecommunication systems, and the list could go on indefinitely although a few procedures described may have to be modified for the problem of interest.

One final comment should be made regarding a validation of the TIES method. The likelihood of entire method being validated is minute. To validate the entire method, one would have to obtain the data and information regarding the decisions, configurations, and technology options throughout an existing system. Unfortunately, most companies do not retain the detailed information regarding previous designs and how the development process evolved from concept formulation to product launch.

Nonetheless, elements of the TIES method may be validated. In particular, the M&S environment may be validated to experimental or flight data. Specifically, if one were to model an existing system in the environment, the aerodynamics, component weights, and the performance of the system could be calibrated to the actual data of that system if the information could be obtained from the original airframe and engine manufacturer. Additionally, if metamodels of higher fidelity analysis tools are inserted into the M&S environment, the metamodels could also be verified with a comparison to experimental or flight data. Another element to be validated is the accuracy of a metamodel representation of the customer requirements as obtained from the M&S environment. One approach for validation would be a comparison of randomly generated evaluations of customer requirements to the values obtained from the metamodels. Finally, the additive nature could be validated with mock-up systems that incorporated two or more technologies and then in isolation to determine the individual effects and the combined effects.

CHAPTER IV

IMPLEMENTATION

The Technology Identification, Evaluation, and Selection (TIES) method developed in Chapter III was applied to a High Speed Civil Transport (HSCT) as a proof of implementation. This concept has received worldwide attention since interest was renewed in the commercial industry during the mid-1980's. This vehicle was a perfect benchmark application for the TIES method due to the technically challenging customer requirements and the need for revolutionary advances over present day technological capabilities. The first example presented is an initial application of the entire method and is followed by an example that changes the technology assumptions to demonstrate the robustness of the method.

Example 1: Full Application of the TIES Method

Step 1: Define the Problem

Voice of the Customer

Travelers have always welcomed the idea of reaching distant destinations in less time without having to spend a great deal of money. However, with the exception of the Concorde, the speed of commercial aircraft has not significantly increased over the last 30 years due to the enormous technical difficulties associated with faster-than-sound travel. During the late 1960's, an attempt to create a supersonic commercial transport aircraft resulted in the Concorde, which entered into service in 1975. Although the Concorde was a technological triumph, it was less than an economic success. The ticket fare (approximately \$6,500 for New York to London [102]) was as much as eight times higher than comparable commercial subsonic transports. At the time of its inception, the Concorde represented an innovative solution to one of the most challenging commercial endeavors, that of supersonic transportation. However, this concept had many shortcomings: poor reliability, high specific fuel consumption, and low payload capacity [103]. Moreover, the Concorde does not adhere to any of the environmental restrictions imposed in recent years, such as NO_x emission and FAR 36 Stage III noise requirements.

From a manufacturer's point of view, the Concorde was a challenging task full of technological unknowns that forced a move into uncharted territories. This led to over-designing that increased the weight and cost of the final aircraft in order to avoid unexpected surprises. As a result, the Concorde received a weak response from commercial airlines that were reluctant to accept the high acquisition price and narrow or

non-existent profitability. In addition, market studies indicated that the required ticket fare for this aircraft was too high for most passengers to pay (average required yield per Revenue Passenger Mile, \$/RPM \approx \$0.8). The engine's poor reliability record has also contributed to the poor operational performance.

In addition, recognition of the environmental impact of high flying aircraft to the upper atmospheric ozone concentration resulted in de-facto limitations on the emission of certain compounds, most notably nitrous oxides, NO_x. At the time of the Concorde's inception, the upper atmospheric impact was not an issue; therefore, it was not designed to meet any type of emissions standard. Also, the Concorde is currently powered by four Rolls-Royce Olympus 593 Mk610 turbojet engines, which are inherently noisy. Consequently, most airports have been forced to ban the Concorde due to noise complaints from surrounding residential neighborhoods.

Since the introduction of the Concorde in 1975, many changes have occurred in technology readiness and the international air travel market. Some researchers predict that current technology has reached a stage where it may be possible to build a commercially viable supersonic aircraft. Furthermore, the Concorde is expected to reach its life-cycle limit within the next five to ten years. In addition, the number of people traveling abroad has increased rapidly [21,22]. These changes warrant a very serious re-examination of the market and technological potential for a second-generation supersonic transport [104].

A High Speed Civil Transport (HSCT) is the United States' response to this growing need for a next-generation supersonic aircraft. The most evident benefit that an HSCT brings to the traveling community is the travel time reduction resulting from flying at

high supersonic speeds. The travel time for a passenger on a typical New York to Paris flight can be reduced by as much as 65% [105]. Such time savings would have a strong appeal to the business executive. The increase in international flights for business interactions would promote the "door-to-door" policy [106] that seems to be dwindling in the cyberspace era of e-mail, faxes, and modems. An HSCT concept would have an enormous impact for the country that produced the aircraft. The United States, if it were to produce this vehicle, could ensure that aerospace technical superiority remained within the U.S. and provide an estimated 140,000 jobs [107,108] for a \$200 billion HSCT market to stimulate the aerospace industry.

The greatest challenge facing an HSCT is the necessity to go farther, with a greater payload capacity, than the Concorde at an operating cost for the airline comparable to that of current subsonic transports. This translates to an increase in vehicle range and passenger capacity while minimizing the fuel cost per trip. Furthermore, government research revealed that the success of an HSCT will require significant technological advances in order to provide the needed environmental compatibility and economic viability [25]. Based on the recent NASA High Speed Research program, an HSCT was defined as a Mach 2.4, 300 passenger aircraft with a 5,000-nm range [108] with four mixed-flow turbofan engines [20]. The aircraft is restricted to subsonic flight over land due to the impact of sonic boom and must abide by all FAA regulations. Previous studies have shown that an HSCT was not technically or economically feasible with conventional technologies [109,110,111]; where feasibility was measured by compliance with noise levels, takeoff and landing field length requirements, gross weight limitations, and affordability goals.

Voice of the Engineer

In accordance with the TIES method, the “voice of the customer” previously described was translated into the “voice of the engineer” in the form of quantifiable metrics. For this study, the metrics are summarized in Table VII. The performance metrics were constrained by either FAA regulations (Vapp, FON, and SLN) or airport compatibility requirements (Landing FL, TOFL, and TOGW). Most of the economic metrics, in fiscal year 1996 dollars, were not constrained, but only minimized, with the exception of \$/RPM which had a target value of \$0.10/RPM. Two economic parameters, Direct Operating Costs per trip plus Interest (DOC+I) and Total Airplane Related Operating Costs (TAROC), have recently become important metrics for measuring commercial transport affordability. DOC+I constitutes approximately 55% of the passenger ticket price and includes: flight and cabin crew salaries, engine and airframe maintenance, fuel and APU costs, insurance, depreciation, interest, and landing fees. TAROC is the DOC+I plus ground handling; ground property, maintenance, and depreciation; and ground general and administrative costs, and constitutes an additional 10% of the passenger ticket price.

Table VII: HSCT System Level Metrics

Parameter	Acronym	Target or Constraint	Units
<u>Performance</u>			
Approach Speed	Vapp	≤ 155	kts
FAR Stage II Flyover Noise	FON	≤ 106	EPNLdB
Landing Field Length	LdgFL	$\leq 11,000$	ft
FAR Stage II Sideline Noise	SLN	≤ 103	EPNLdB
Takeoff Field Length	TOFL	$\leq 11,000$	ft
Takeoff Gross Weight	TOGW	$\leq 1,000,000$	lbs
<u>Economics</u>			
Acquisition Price	Acq\$	<i>Minimize</i>	FY96 \$M
Research, Development, Testing, and Evaluation	RDT&E	<i>Minimize</i>	FY96 \$M
Average Required Yield per Revenue Passenger Mile	\$/RPM	≤ 0.10	FY96 \$
Total Airplane Related Operating Costs	TAROC	<i>Minimize</i>	FY96 ¢
Direct Operating Costs plus Interest	DOC+I	<i>Minimize</i>	FY96 ¢

Step 2: Define Concept Space

Alternative Concept Space

The next step was to define the two concept spaces, the space of alternatives and the design space. First, the space of alternatives was created with the aid of a Morphological analysis. The Concorde was taken as the starting point for system decomposition and thus defined the class of vehicles to investigate. For example, the Concorde has an area-ruled fuselage, while alternative fuselage characteristics include traditional cylinders or an oval shape. This process of decomposing the system was performed via brainstorming sessions and formalized in a Morphological Matrix. A sample of the HSCT matrix utilized in this investigation is shown in Figure 34. To quantify the feasibility space, a

baseline datum point was established from this matrix. This datum was assumed to be the combination of alternatives which represent conventional (or present day) technologies and are the circled characteristics in Figure 34.

Based on the problem definition of the customer requirements in Step 1, the configurations analyzed in this study were sized for a 5,000-nm mission with the primary cruise altitude of 67,000 ft at Mach 2.4. A subsonic cruise portion precedes the primary cruise segment at an altitude of 35,000 ft at Mach 0.9, as depicted in Figure 35. The mission was consistent with recent industry investigations. The payload of the aircraft was assumed to be 300 passengers and baggage, flight crew of two, nine flight attendants, and a fuselage length of 310 ft with a maximum diameter of 16 ft at the wing apex and trailing edge.

Alternatives Characteristics		1	2	3	4
Config	Vehicle	Wing & Tail	Wing & Canard	Wing, Tail & Canard	Wing
	Fuselage	Cylindrical	Area Ruled	Oval	
	Pilot Visibility	Synthetic Vision	Conventional	Conventional & Nose Droop	
Mission	Range (nmi)	5000	6000	6500	
	Passengers	250	300	320	
	Mach Number	2	2.2	2.4	2.7
Propulsion	Type	MFTF	Turbine Bypass	Mid Tandem Fan	Flade
	Materials	Conventional	High T Comp		
	Combustor	Conventional	RQL	LPP	
	Nozzle	Conventional	Internal Flow Alteration	Mixed Ejector	Mixer Ejector & Acoustic Liner
Aero	Low Speed	Conventional Flaps	Conventional Flaps & Slots	C C	
	High Speed	Conventional	NLFC	Active Control	HLFC
Struct	Materials	Aluminum	Titanium	High Temp. Composite	
	Process	Integrally Stiffened	Spanwise Stiffened	Monocoque	Hybrid

Figure 34: HSCT Alternative Concepts Space

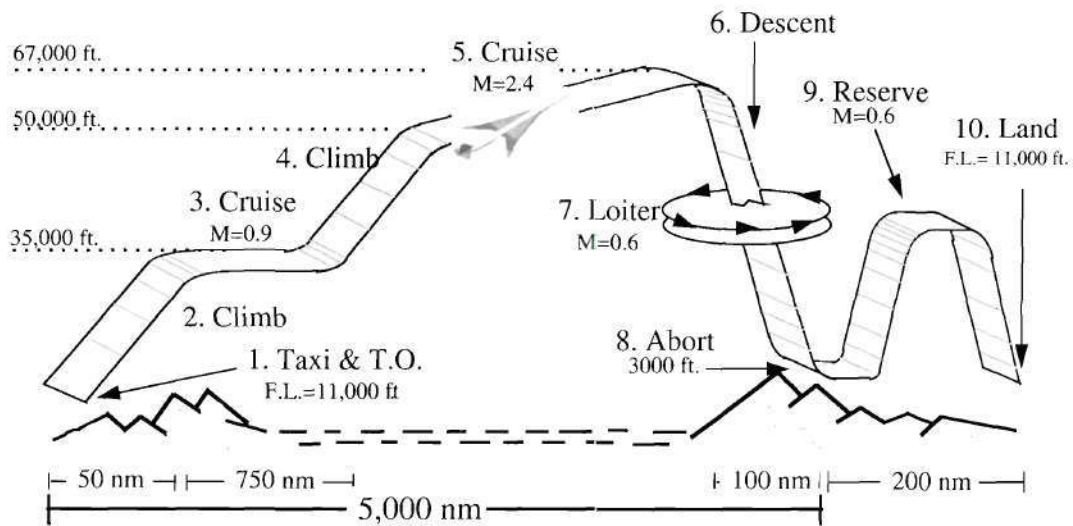


Figure 35: HSCT Mission Profile

Design Space

The alternative concepts defined in the Morphological Matrix were further decomposed into product attributes. These attributes were the key geometric and propulsive design variables which defined the design space of interest and directly affected the metric values. The design variables are listed in Table VIII, along with the associated ranges of interest. The geometric ranges were based on a trial-and-error approach to capture the widest range of configurations, from a pure arrow wing to a standard double-delta. Samples of the various wing planforms captured in the defined ranges are shown in Figure 36. The propulsive ranges were defined to push the state-of-the-art in propulsion technologies. The non-dimensional wing parameters, such as X2 and X3, will be described in Step 3. The baseline configuration used to start the TIES method is listed in Table IX and displayed in Figure 37 and is representative of recent HSCT investigations.

Table VIII: HSCT Design Space

Variable	Minimum	Maximum	Units	Description
SW	7500	9000	ft ²	Wing Area
TWR	0.29	0.33	~	Thrust-to-weight ratio
TIT	3000	3400	°R	Turbine Inlet Temperature
FPR	3.5	4.5	~	Fan Pressure Ratio
OPR	18	21	~	Overall Pressure Ratio
CLdes	0.08	0.12	~	Design Lift Coefficient
X2	1.54	1.69	~	LE kink x-location*
X3	2.1	2.36	~	LE tip x-location*
X4	2.4	2.58	~	TE tip x-location
X5	2.19	2.37	~	TE kink x-location*
X6	2.18	2.5	~	TE root x-location*
Y2	0.44	0.58	~	LE kink y-location*
t/c_root	3	5	%	Wing root thickness-to-chord ratio
t/c_tip	2	4	%	Wing tip thickness-to-chord ratio
SHref	400	700	ft ²	Horizontal Tail Area
SVref	350	550	ft ²	Vertical Tail Area

*Variable normalized by wing semi-span

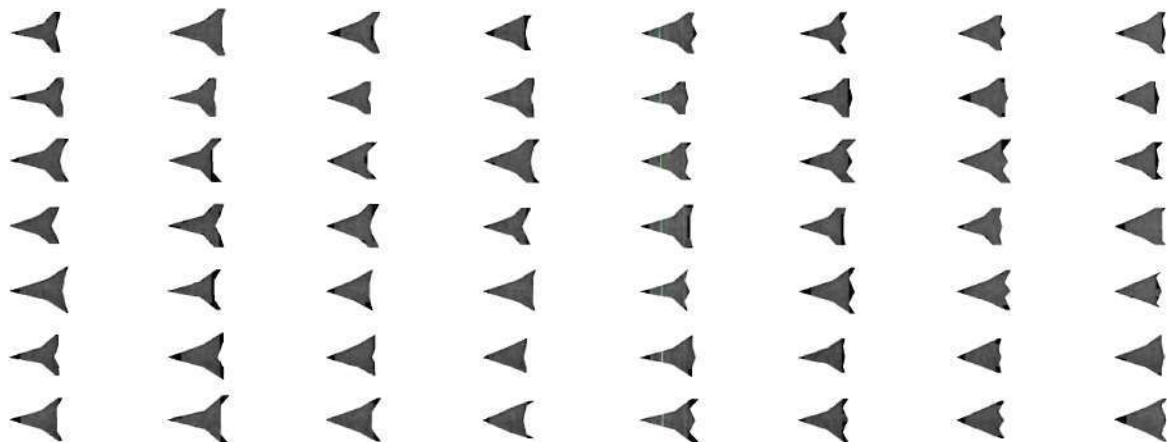


Figure 36: Sample HSCT Wing Planforms

Table IX: HSCT Baseline Description

Variable	Value	Units	Description
SW	9000	ft ²	Wing Area
TWR	0.29	~	Thrust-to-weight ratio
TIT	3000	°R	Turbine Inlet Temperature
FPR	4.5	~	Fan Pressure Ratio
OPR	18	~	Overall Pressure Ratio
CLdes	0.1	~	Design Lift Coefficient
X2	1.609	~	LE kink x-location
X3	2.36	~	LE tip x-location
X4	2.58	~	TE tip x-location
X5	2.19	~	TE kink x-location
X6	2.18	~	TE root x-location
Y2	0.51	~	LE kink y-location
t/c_root	4	%	Wing root thickness-to-chord ratio
t/c_tip	3	%	Wing tip thickness-to-chord ratio
SHref	550	ft ²	Horizontal Tail Area
SVref	450	ft ²	Vertical Tail Area

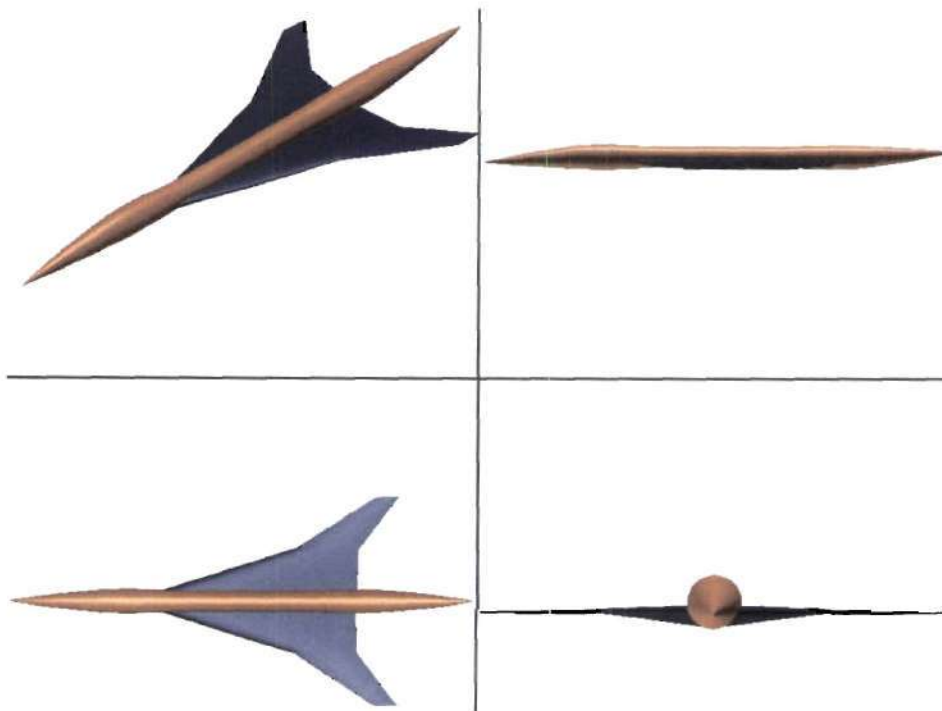


Figure 37: HSCT Baseline Configuration

Step 3: Modeling and Simulation

The metrics, as influenced by the concept spaces, were quantitatively assessed via a Modeling and Simulation (M&S) environment. This environment was created with the aid of the public domain synthesis and sizing tool FLOPS (FLight OPTimization System) linked to the life cycle cost code ALCCA (Aircraft Life Cycle Cost Analysis). FLOPS [112] was chosen for this research due to its ability to fulfill the guidelines of an M&S environment set forth in Chapter III. FLOPS is a public domain tool developed by the NASA Langley Research Center. FLOPS consists of nine modules including weights, aerodynamics, engine cycle analysis, propulsion data scaling and interpolation, mission performance, takeoff and landing, noise footprint, cost analysis, and program control. FLOPS is a fairly robust M&S code with regards to subsonic commercial aircraft. For military systems, a NASA Ames Research Center developed analysis tool called AIRcraft SYNThesis, ACSYNT [113], is a more appropriate tool. However, the cost module in FLOPS, as developed by Johnson [112], is a top-level costing method and was replaced with a more detailed module called ALCCA [114]. ALCCA is comprised of a series of modules capable of predicting aircraft economic parameters, such as acquisition cost, ROI for the airline and manufacturer, cash flows, and operating costs. ALCCA was integrated into FLOPS so that immediate knowledge of the affordability aspects, as affected by the various designs, could be determined. The integration of these two tools represents a directly linking higher fidelity tools to overcome analysis deficiencies.

Additionally, due to the non-conventional nature of an HSCT configuration, many of the historically based, regressed equations within FLOPS were neither accurate, nor valid. In particular, the aerodynamics, wing weight, and noise calculations were

incapable of predicting an HSCT concept with a sufficient confidence. The M&S capabilities were enhanced through the use of metamodels that approximated more sophisticated analysis tools. These metamodels, in the form of second order RSEs, were inserted into the FLOPS source code. Mavris and Haden provided the structural enhancements [115]. The sideline and flyover noise calculations were based on RSEs created by Olson [116], and the aerodynamic RSEs were enhanced from the original model presented by DeLaurentis [87]. The enhancements included: an increase in the number of variables forming the RSEs, inclusion of the vertical tail, different wing thickness-to-chord ratios at the root and tip, and slight modifications to the variable ranges. The aerodynamic RSEs were of the form:

$$C_D = C_{D_0} + K_1 C_L + K_2 C_L^2 \quad (35)$$

where C_{D_0} was a function of operating Mach number, altitude, and geometric variables; K_1 and K_2 were functions of operating Mach number and geometric variables. The variables utilized to generate the RSEs are depicted in Figure 38. A screening test was performed with these variables for the subsonic and supersonic operating regimes for a design point of Mach 2.4, top-of-climb, and a lift coefficient as defined by the corresponding DoE case. Maximums of 15 and 16 variables were used for each coefficient in Equation 35 for each Mach-altitude combination and are described in more detail by Mavris [117]. The 15 and 16 variable DoE employed for the RSEs was a custom-made face-centered CCD, with a Resolution IV fractional factorial design described previously. The important variables forming the subsonic and supersonic coefficients of Equation 35 consisted of the geometric variables in Table VIII in addition

to those listed in Table X. The aerodynamic analysis tools utilized to estimate the RSE coefficients are listed in Table XI. Once the M&S environment was created, the baseline concept metrics were quantified for the and summarized in Table XII.

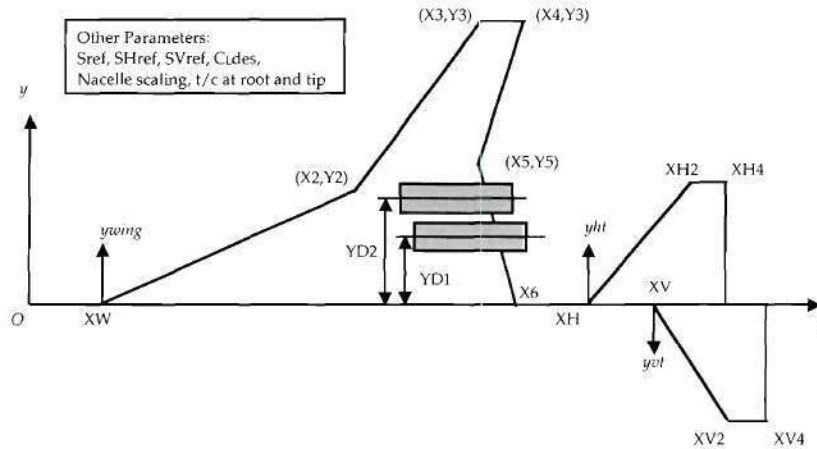


Figure 38: HSCT Aerodynamic RSE Variables

Table X: Extra Aerodynamic RSE Variables

Variable	Minimum	Maximum	Description
XW	0.22	0.28	Wing apex location on fuselage
Y5	0.43	0.6	TE kink y-location*
NACSCAL	0.9	1.1	Percent nacelle scaling
YD2**	0.49	0.55	Outboard nacelle location

* Variable normalized by the wing semi-span,

** Variable only used for supersonic regime

Table XI: Aerodynamic Analysis Tools

Tool	Purpose
AERO2s [118]	Low speed induced drag
AWAVE [119]	Fuselage area-ruling distribution
BDAP [119]	Skin friction and wave drag
VORLAX [120]	Subsonic and supersonic induced drag
WingDes [118]	Optimal wing twist and camber for given design lift coefficient

Table XII: HSCT Baseline Metrics

Parameter	Acronym	Value
Performance		
Approach Speed	Vapp	154.1 kts
FAR Stage II Flyover Noise	FON	112.3 EPNLdB
Landing Field Length	LdgFL	9,063.2 ft
FAR Stage II Sideline Noise	SLN	111.6 EPNLdB
Takeoff Field Length	TOFL	12,407 ft
Takeoff Gross Weight	TOGW	937,108 lbs
Economics		
Acquisition Price	Acq\$	218.58 FY96 \$M
Research, Development, Testing, and Evaluation	RDT&E	16,124.9 FY96 \$M
Average Required Yield per Revenue Passenger Mile	\$/RPM	0.1236 FY96 \$
Total Airplane Related Operating Costs	TAROC	5.948 FY96 ¢
Direct Operating Costs plus Interest	DOC+I	5.058 FY96 ¢

Step 4: Investigate the Design Space

The design space of the conventional configuration, i.e., the baseline concept, was initially investigated using the second probabilistic method – metamodel representation of the analysis code combined with a Monte Carlo Simulation. This investigation was performed to determine if a feasible space existed and, if so, determine how large the area was; otherwise, the investigation would determine which constraints were prohibitive or “show-stoppers” to an HSCT concept. The design space under investigation was created by the control variables listed in Table VIII. These parameters varied uniformly between the stated minimum and maximum values to provide data whereby a quadratic RSE of the metrics listed in Table VII were approximated. The 16 variable DoE described in Step 3 was utilized to build these models. The combined FLOPS and ALCCA code was

executed using the variable values prescribed by the DoE, appropriate data extracted, and the RSEs formed with the statistical software, JMP®. The primary economic analysis assumptions made for this study are listed in Table XIII. The production quantity was assumed to be 800 units and all cost figures were for 1996 fiscal year dollars.

A plethora of information was gathered from exploring the design space with an RSM approach, in particular, the sensitivity of metrics to the design variables, upper and lower limits of the metrics, and an optimal geometric configuration were facilitated with the JMP® software.

Table XIII: Economic Assumptions

Parameter	Value	Parameter	Value
Airframe spares (% of airframe price)	6%	Fiscal year dollars	1996
Airline ROI	10%	Fuel cost	\$0.70/gal
Average annual inflation	8%	Hull insurance (% aircraft price)	0.35%
Depreciation residual value	10%	Manufacturer learning curve	78%
Downpayment	0%	Passenger load factor	65%
Economic life	20 years	Maintenance burden (% direct labor)	200%
Economic range	5000 nm	Maintenance labor rate	\$25/hr
Engine spares (% of engine price)	6%	Manufacturer ROI	5%
Engine units produced	4000 units	Airframe production quantity	800 units
Engineering labor rate	\$89.68/hr	Tooling labor rate	\$54.68/hr
Entry into service date	2006	Utilization	5000 hr/yr
Financing period	20 years	Years of production	15 years

A summary of fit analysis, such as R^2 , was employed to ensure that the metamodel fit was acceptable. As a general rule of thumb, an R^2 value greater than 90% represents a good model fit [121]. All metric RSEs had an R^2 value greater than 99%. To further validate the accuracy of the RSEs, Bandte suggests that an extensive test at randomly distributed points within the design space should be evaluated and compared to the RSEs [35]. Although the computational effort was increased, the investigation provided indisputable evidence as to the accuracy of the RSM approach. The original DoE utilized to create the RSEs required 289 analysis code executions; thus, 289 random cases were executed and compared to the original models. For a perfect approximation of an analysis code, the predicted value should equal the actual value for every metric. If one were to plot these values against each other, a straight line with a slope of one would be obtained if the approximation were perfect. Any deviations from this trend indicated error in the model. The TOFL and \$/RPM confirmation investigations are depicted in Figure 39. The perfect model fit trend line is shown along with bounds of the model error. For each metric, the predicted and actual values were compared with a maximum of $\pm 5\%$ error. The largest RSE error stemmed from interactions amongst variables that were highly quadratic, such as the wing area (SW) interacting with turbine inlet temperature (TIT). For metrics that were purely linear, the error of the RSE was minimal, while mild quadratic and interaction effects produced moderate errors on the order of $\pm 2-3\%$. In the conceptual stage of design, $\pm 5\%$ error was considered acceptable. The validation results were consistent with the guidelines for selecting an appropriate probabilistic design technique as listed in Table IV and for validating portion of the TIES method.

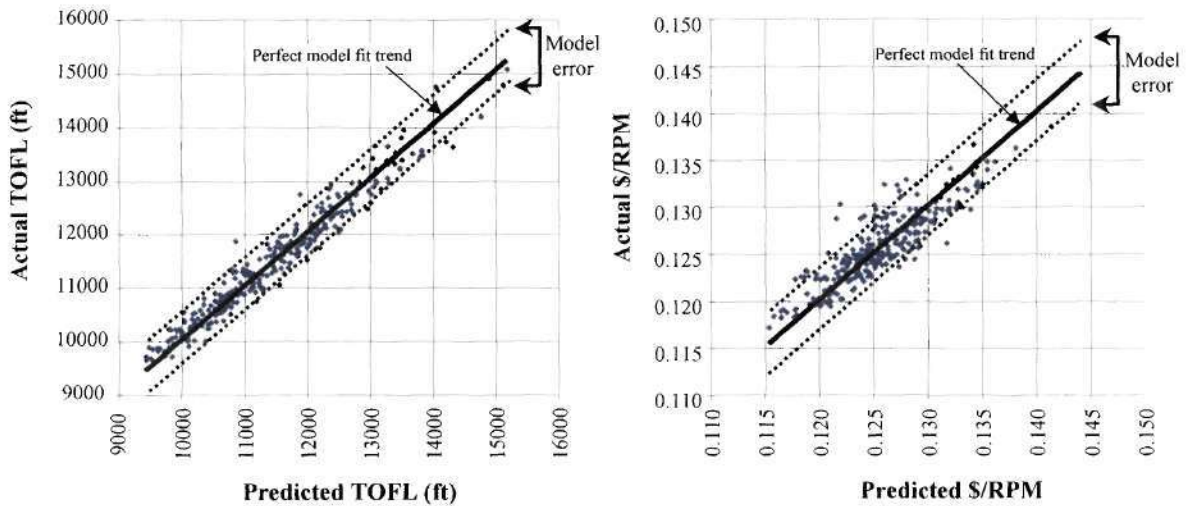


Figure 39: RSE Accuracy Determination

Metric Sensitivities

One of the outputs that results from Step 4 was a prediction profiler of the metrics as a function of the design variables as shown in Figure 40. Only the constrained metrics are shown for clarity. All metrics were highly sensitive to the influence of wing area, thrust-to-weight ratio, the spanwise location of the leading edge kink (Y2), and the thickness-to-chord ratio at the tip of the wing as shown by the large prediction trace slopes. Furthermore, the edges of the design space were readily identified by the upper and lower values for each metric. Some combination of design variable settings resulted in an upper limit in TOFL of 17,340 ft and a lower limit of 8,625 ft. Thus, some combination of design variables would satisfy the 11,000 ft constraint. However, the lower limit of the SLN and the \$/RPM do not satisfy the required constrained values or 103 EPNLdB and \$0.1/RPM, respectively.

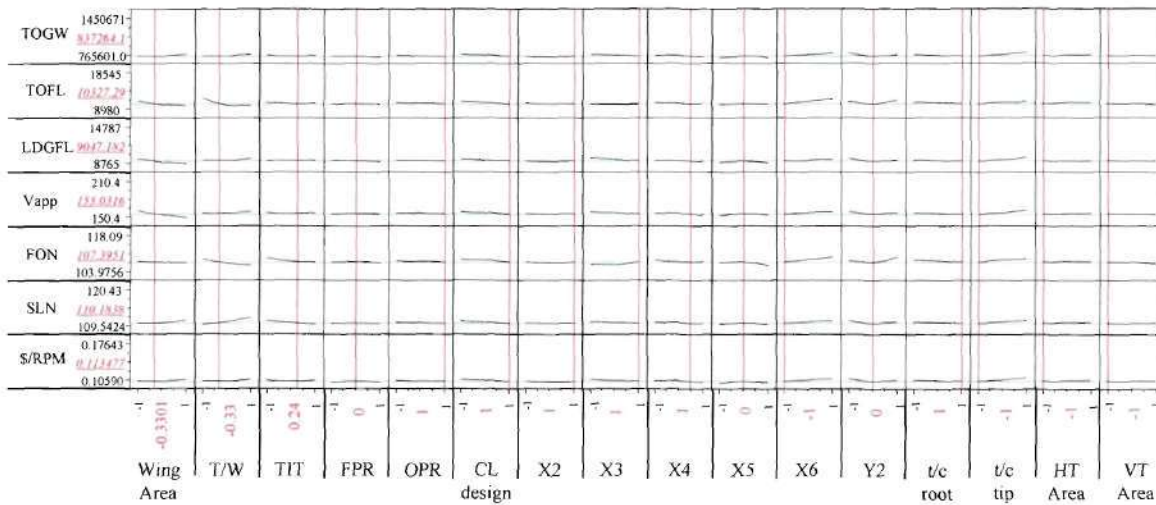


Figure 40: HSCT Design Space Prediction Profiler

Design Space Optimization

The prediction profiler revealed that no feasible design space existed due to the violation of the SLN and \$/RPM constraints. Yet, which design variable settings most closely satisfied all the metric constraints? The desirability feature of JMP[®] facilitated this objective. The desirability feature, which translates a multi-objective problem to one objective in the form of a “desirability” function was pioneered by Derringer and Suich [122]. Consider the prediction profiler illustrated in Figure 40. There were seven different constrained objective functions (i.e., metrics) defined on the ordinate. The SLN and \$/RPM were not constrained in this process due to complete violation of the constraint values. The violation was determined based on the lower limit of the metrics on the profiler of $SLN \geq 109.54$ EPNLdB and $$/RPM \geq \0.1059 . Thus, SLN and \$/RPM were minimized. The profiler was manipulated until the desirability objective was maximized. The variable settings that maximized the desirability are listed in Table XIV and the resulting metric values are in Table XV. A geometric comparison of the original baseline

(solid model) to the optimal geometry (wireframe model) is depicted in Figure 41. As is evident, the optimal geometry had a much smaller wing area and a larger inboard leading edge sweep. The trailing edge for the optimal geometry was swept back while the original baseline was blunt. The optimal configuration reduced all performance metrics except for V_{app} which was slightly increased due to a higher wing-loading. All economic metrics were reduced due to the dependency of the economic evaluations on the component weights of the vehicle. Since the optimal configuration was almost 100,000 pounds lighter, the corresponding economic metrics were also lower.

Table XIV: Optimal HSCT vs. Baseline Description

Variable	Optimized Baseline	Original Baseline	Units	Description
SW	8070	9000	ft ²	Wing Area
TWR	0.31	0.29	~	Thrust-to-weight ratio
TIT	3312	3000	°R	Turbine Inlet Temperature
FPR	4	4.5	~	Fan Pressure Ratio
OPR	21	18	~	Overall Pressure Ratio
CLdes	0.12	0.1	~	Design Lift Coefficient
X2	1.615	1.609	~	LE kink x-location
X3	2.36	2.36	~	LE tip x-location
X4	2.58	2.58	~	TE tip x-location
X5	2.37	2.19	~	TE kink x-location
X6	2.18	2.18	~	TE root x-location
Y2	0.4659	0.51	~	LE kink y-location
t/c_root	5	4	%	Wing root thickness-to-chord ratio
t/c_tip	2	3	%	Wing tip thickness-to-chord ratio
SHref	400	550	ft ²	Horizontal Tail Area
SVref	350	450	ft ²	Vertical Tail Area

Original Baseline (solid model)
Optimized Baseline (wireframe model)

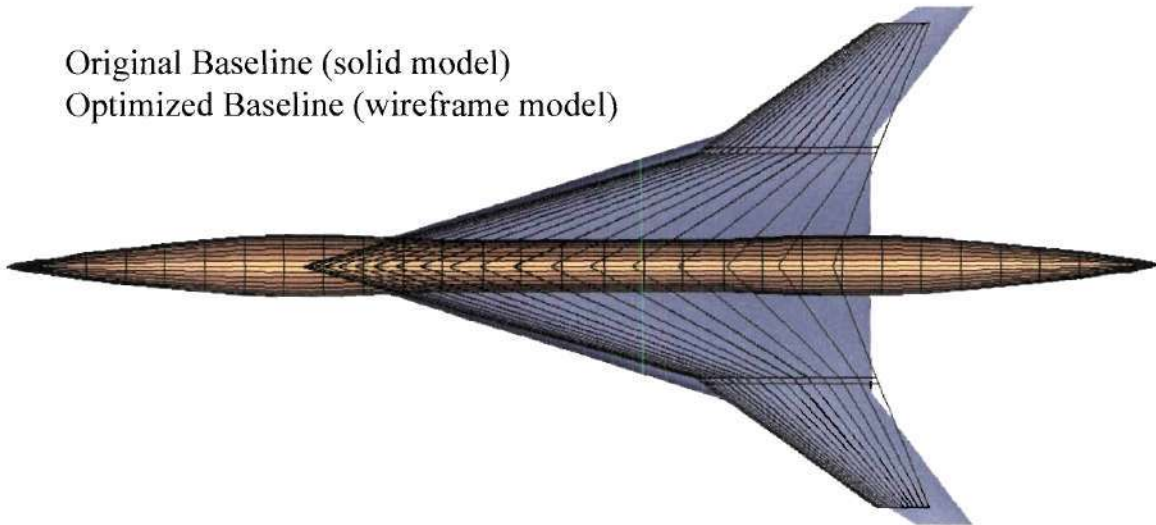


Figure 41: Comparison of Optimal and Original HSCT Geometry

Table XV: Optimal HSCT Metrics

Parameter	Original Baseline	Optimal Configuration
<u>Performance</u>		
V _{app}	154.1 kts	155.03 kts
FON	112.3 EPNLdB	107.3 EPNLdB
LdgFL	9,063.2 ft	9,047.2 ft
SLN	111.6 EPNLdB	110.2 EPNLdB
TOFL	12,407 ft	10,327 ft
TOGW	937,108 lbs	837,264 lbs
<u>Economics</u>		
Acq\$	218.58 FY96 \$M	207.89 FY96 \$M
RDT&E	16,124.9 FY96 \$M	15,076.9 FY96 \$M
\$/RPM	0.1236 FY96 \$	0.1135 FY96 \$
TAROC	5.948 FY96 ¢	5.354 FY96 ¢
DOC+I	5.058 FY96 ¢	4.535 FY96 ¢

Carpet Plots

If the decision-maker had the option to negotiate the constrained metrics, how much constraint relaxation would be needed to create a feasible space? A carpet plot of the design space was created with the Contour Profiler feature of JMP[®]. The optimal configuration was used and the metrics were deviated until a feasible space was obtained. If the \$/RPM was relaxed by 15%, the FON by 1%, and the SLN by 7.5%, a small feasible space emerged, as shown in Figure 42.

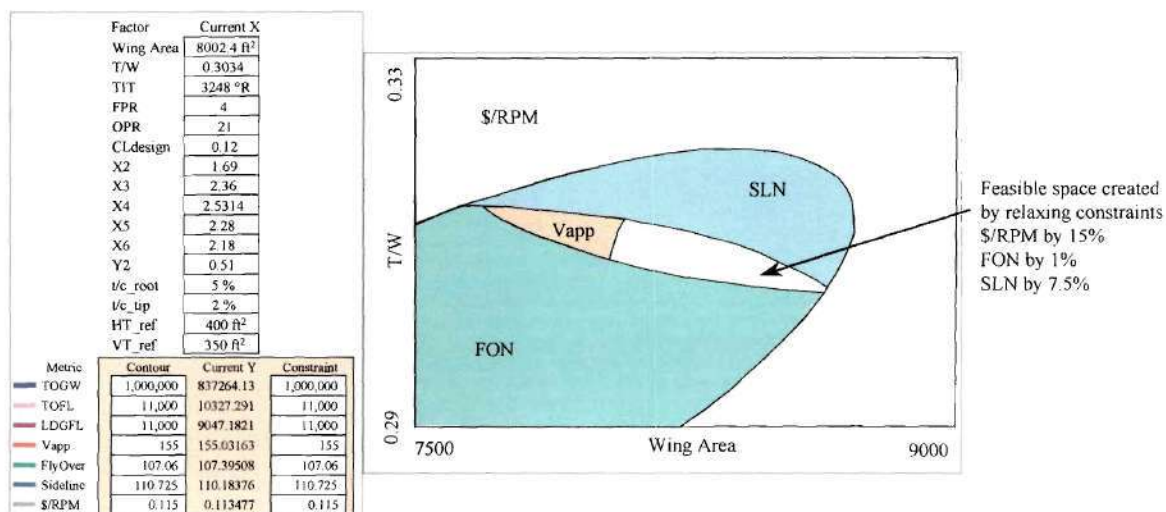


Figure 42: Feasible Space for “Negotiated” Metrics

Probabilistic Design Space

The design space information discussed above is analogous to the information obtained from traditional design approaches. A key difference of a probabilistic approach is the investigation of the whole design space. Thus, once the RSEs were generated and validated, a Monte Carlo Simulation was performed on each equation with the software package Crystal Ball[®]. The random number generator in Crystal Ball[®] generated values for the design variables in Table VIII based on assumed uniform distributions. Crystal

Ball[®] used the design variable settings to determine the metric values through the RSEs. This procedure was repeated 10,000 times to obtain the CDFs of the design space for each metric. The results were extracted in 5% confidence intervals and used to determine the HSCT system feasibility in Step 5.

Step 5: Determine System Feasibility

No feasible space existed due to the violation of SLN as depicted in Figure 40 by the lower bound value of SLN. However, the location of the design space relative to the metric targets should be of importance to the decision-maker and will quantify exactly how much improvement is needed. A CDF displays the probability or confidence of achieving values less than or greater than a given amount [45]. With the metric CDFs, the probability of meeting a metric constraint was readily identified. If no feasible space existed, how much needed improvement was determined from a calculation of how far the CDF was from the target. For the metrics listed in Table VII, seven were constrained.

The design space investigation performed in Step 4 resulted in the probability values of the amount of feasible space as listed in Table XVI and depicted in Figure 43. Some of the design space satisfied the performance constraints: LdgFL of 87.1%, TOGW of 55.5%, etc. Yet, the sideline noise (SLN) had a 0% probability of meeting the 103 EPNLdB constraint. The SLN was the performance “show-stopper” to the HSCT concept and needed significant improvement to create a feasible space as seen in Figure 43, especially since EPNLdB is a logarithmic scale. To create at least a 25% feasible space, an 8.79% reduction in SLN was needed. Further, the design space was not economically viable due to the violation of \$/RPM. Obviously from the feasibility study, infusion of technologies was needed and quantitatively supported claims made previously.

Table XVI: HSCT System Feasibility Needed Improvements

Metric	Objective, Constraint	Units	Baseline Value	Needed % Reduction for Baseline	Needed % Reduction for 25% Feasible	% of Feasible Space
TOGW	$\leq 10^6$	lbs	937,108	Ok	Ok	55.5
TOFL	$\leq 11,000$	ft	12,407	-12.79	-2.17	18.7
LdgFL	$\leq 11,000$	ft	9,063	Ok	Ok	87.1
Vapp	≤ 155	kts	154.1	-5.94	-4.34	3.3
FON	≤ 106	EPNLdB	112.3	-1.34	-2.44	3.1
SLN	≤ 103	EPNLdB	111.6	-8.37	-8.79	0
Acq\$	Reduce	FY96 \$M	218.6	Nominal	Nominal	~
RDT&E	Reduce	FY96 \$M	16,124.9	Nominal	Nominal	~
\$/RPM	≤ 0.1	FY96 \$	0.1235	-23.56	-26.34	0
TAROC	Reduce	FY96 ¢	5.948	Nominal	Nominal	~
DOC+I	Reduce	FY96 ¢	5.058	Nominal	Nominal	~

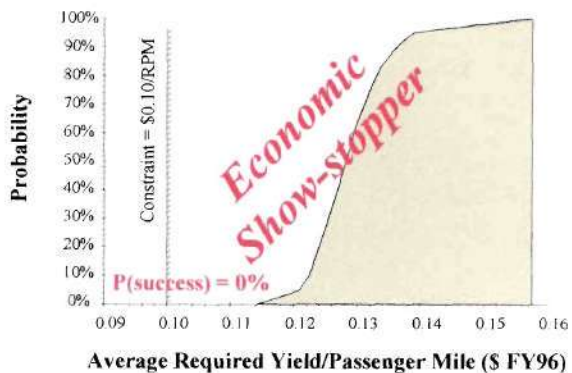
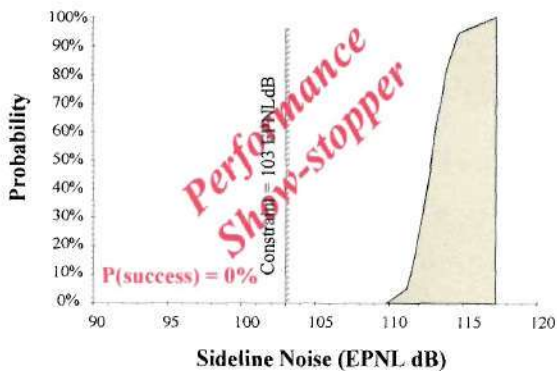
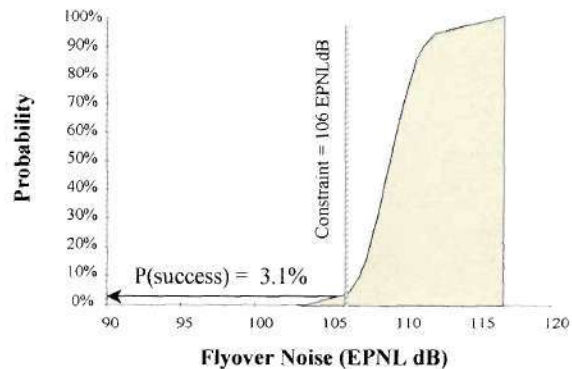
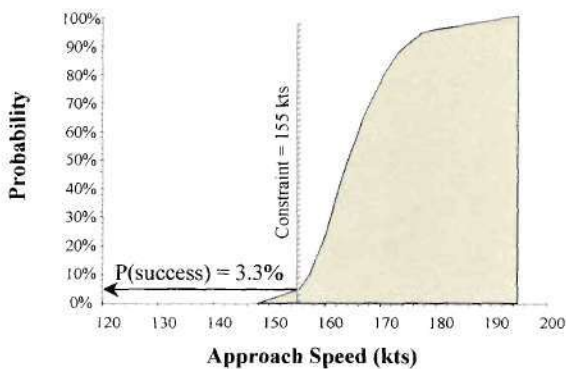


Figure 43: System Feasibility Investigation

Step 6: Technology Identification

Since the probability of success for system feasibility and viability was non-existent for the SLN and the \$/RPM, new technologies were needed to potentially create a feasible and viable space. The configuration for which technologies were infused was the optimal configuration established in Step 4. However, the original design space investigation did not take into account the pilots' visibility during landing conditions. Thus, a 12,000 lb weight penalty was applied to the optimal configuration fuselage weight to simulate the addition of a nose droop, similar to the Concorde, for pilot visibility. This resulted in a needed improvement of 7.28% in SLN to achieve a feasible space and slightly modified all other metrics. The system feasibility investigation showed that the SLN constraint was the most detrimental performance metric to an HSCT concept. Consequently, technologies that specifically address noise reduction must be identified. Additionally, any technologies or technology programs that might reduce the total weight of the vehicle were also considered due to the violation of \$/RPM.

Eleven technologies and technology programs were considered for infusion. The technologies along with the primary purposes were identified through a literature search of potential sub-component alternatives as identified in Step 2 in the Morphological Matrix and are listed in Table XVII. The smart wing structures (T9), active flow control (T10) and active acoustic control (T11) were technologies under NASA's Aircraft Morphing program [123]. Two engine technology concepts, environmental engines (T5) and active acoustic control (T11), were considered since they are predicted to improve engine noise characteristics. The TRLs were established by comparing the status of technology research in 1998 to the definitions in Table VI.

Table XVII: Alternative Technologies

(Identifier) Technology	TRL	Primary Purpose
(T1) Composite Wing [124]	3	Wing weight reduction
(T2) Composite Fuselage [124]	3	Fuselage weight reduction
(T3) Circulation Control [125,126]	4	Increased low speed performance
(T4) Hybrid Laminar Flow Control [60]	3	Cruise drag reduction
(T5) Environmental Engines [20,110,111]	3	Reduce noise, fuel burn, and emissions
(T6) Advanced Flight Deck Systems [108]	4	Synthetic vision removes fuselage nose droop weight penalty
(T7) Advanced Propulsion Materials [127]	3	High temp. materials, reduced engine weight, lower fuel burn
(T8) Integrally Stiffened Aluminum Wing Structure [128]	4	Wing weight and part complexity reduction
(T9) Smart Wing Structures [123]	3	Reduced flutter and wing weight
(T10) Active Flow Control [123]	3	Cruise drag reduction
(T11) Active Acoustic Control [123]	3	Noise suppression

Compatibility Matrix

A full factorial combination of the 11 technologies resulted in 2,048 combinations. However, some combinations were not physically realizable. In order to keep non-realistic combinations from biasing the results, a Technology Compatibility Matrix (TCM) was created. The compatibility rules for these technologies were determined from brainstorming activities and are compiled in the TCM in Figure 44. There were twelve combinations of technologies that were deemed incompatible, either from competing for the same purpose or due to extreme degradation effects. Each of the incompatible technology combinations is discussed below. As a result of applying the compatibility logic, the number of alternatives was reduced from 2,048 to 272 combinations.

T1 & T4: Due to the nature of composite structures, the micro-holes needed for HLFC boundary layer suction would severely compromise the composite matrix and create structural integrity problems.

T1 & T8: Competing wing material technologies.

T1 & T9: Smart wing structures require that the wing be deformed to actively change the loads, which would compromise the structural integrity of the composite structure.

T1 & T10: Active flow control requires manipulation of the wing surface to optimally distribute loads and would compromise the composite structure.

T1 & T11: The engine concept is part of the aircraft morphing program. Within the context of the definition of this technology, airframe noise reduction techniques were also utilized within T11 by modification of the wing structure. This would reduce the potential area for which composite wing structures could be used, thus minimizing the impact of T1.

T4 & T8: The integrally stiffened wing structure would inhibit easy maintenance and repair of the HLFC system due to ducting required in the wing structure for HLFC, which would degrade the integrally stiffened wing structure.

T4 & T9: Smart wing structures require the wing may be deformed to actively change the loads, which would compromise the micro holes of HLFC.

T4 & T10: Competing wing drag reduction technologies.

T5 & T11: Competing engine technology concepts.

T6 & T9: Both technology concepts would require a significant computer architecture and system redundancy and would likely have certification difficulties.

T7 & T8: Due to the use of exhaust flaps to direct the exhaust gases from the engine, the trailing edge of the wing is split such that T8 integrity would be compromised.

T8 & T9: Competing wing structures.

Compatibility Matrix (1: compatible, 0: incompatible)		Aircraft Morphing										
		Composite Wing	Composite Fuselage	Circulation Control	HLFC	Environmental Engines	Flight Deck Systems	Propulsion Materials	Integrally, Stiffened Aluminum Airframe Structures (wing)	Smart Wing Structures (Active Aeroelastic Control)	Active Flow Control	Acoustic Control
		T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
Aircraft Morphing	Composite Wing	1	1	1	0	1	1	1	0	0	0	0
	Composite Fuselage		1	1	1	1	1	1	1	1	1	1
	Circulation Control			1	1	1	1	1	1	1	1	1
	HLFC				1	1	1	1	0	0	0	1
	Environmental Engines					1	1	1	1	1	1	0
	Flight Deck Systems						1	1	1	0	1	1
	Propulsion Materials							1	0	1	1	1
	Integrally, Stiffened Aluminum Airframe Structures (wing)								1	0	1	1
	Smart Wing Structures (Active Aeroelastic Control)									1	1	1
	Active Flow Control										1	1
	Acoustic Control											1

Figure 44: HSCT Technology Compatibility Matrix

Technology Impact Matrix

The Technology Impact Matrix (TIM) was constructed for the 11 technologies based on a literature review of the applied research and expert opinions. The TIM, shown in Figure 45, contains the predicted impact values if each technology were matured to the point of full-scale application (TRL of 9). The values shown were assumed to be the “theoretical” upper limits of the technologies. The elements of the technical impact factor vector are listed on the left. The elements encompassed all technology impacts, although not all technologies contributed to every element. The technical “k” vector consisted of

16 elements and was unique for a given technology. The impact values were conservative impacts from the cited references in Table XVII. The technology vector included benefits and degradations to both performance and economic metrics. For example, the infusion of a composite wing could reduce the sized vehicle wing weight by 20% and the cruise drag (due to a smoother wing surface) by 2%. Yet, the costs associated with manufacturing and maintaining this type of wing were more than a conventional aluminum wing structure due to increased complexity. This penalty was simulated with increased Research, Development, Testing, and Evaluation (RDT&E), production, and Operation and Support (O&S) costs. Except for T8 through T11, no explicit economic impacts were found regarding the other technologies. Thus, an educated “guesstimate” impact to the economic metrics was assumed for these technologies.

Technical Impact Factor Vector	Composite Wing	Composite Fuselage	Circulation Control	HLFC	Environmental Engines	Flight Deck Systems	Propulsion Materials	Integrally Stiffened Aluminum Airframe Structures (wing)	Smart Wing Structures (Active Aeroelastic Control)	Active Flow Control	Acoustic Control	Technology Space Limits	
	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	Min	Max
Wing Weight	-20%			+5%				-10%	-5%	+2%		-35%	+7%
Fuselage Weight		-25%				-15%						-40%	0%
Engine Weight				+1%	+40%		-10%				+5%	-10%	+46%
Electrical Weight			+5%	+1%		+2%	+5%		+5%	+2%	+2%	0%	+22%
Avionics Weight				+5%		+2%	+5%		+2%	+5%	+2%	0%	+21%
Surface Controls Weight			-5%						+5%	+5%		-5%	+10%
Hydraulics Weight			-5%						+5%			-5%	+5%
Noise Suppression					-10%		-1%				-10%	-21%	0%
Subsonic Drag	-2%	-2%		-10%						-5%		-19%	0%
Supersonic Drag	-2%	-2%		-15%						-5%		-24%	0%
Subsonic Fuel Flow			+1%	+1%	-2%		-4%				+1%	-6%	+3%
Supersonic Fuel Flow				+1%	-2%		-4%					-6%	+1%
Maximum Lift Coefficient			+15%									0%	+15%
O&S	+2%	+2%	+2%	+2%	+2%		+2%	-2%	+2%	+2%	+1%	-2%	+17%
RDT&E	+4%	+4%	+2%	+2%	+4%	+2%	+4%		+5%	+5%	+5%	0%	+39%
Production costs	+8%	+8%	+3%	+5%	+2%	+1%	+3%	-3%	-3%	-3%	-3%	-12%	+30%

Figure 45: HSCT TIM (Expert Predicted Ideal Values)

One should note that the technologies considered for infusion were considered to be evolutionary technologies. Thus, the eleven technologies fell within the realm of the physics of the M&S environment created in Step 3 and no modifications were necessary. However, if revolutionary technologies were identified and infused, the appropriate physics would need to be modeled within the M&S environment.

As described in Chapter III, the technology space will be created with the use of the RSM in Step 7. Thus, each of the metrics will be defined as a function of the “k” factors. The ranges for which the forthcoming RSEs will be valid are based on the minimum and maximum values of each “k” factor. Following the discussion in Chapter III, the limits were established from a summation of all the reductions of a “k” factor to establish the minimum. Likewise, the maximum was a summation of all the increases as shown by the technology space limits on the right hand side of Figure 45.

TRL Distribution Shapes

The technologies considered for infusion were at a TRL of 3 or 4 based on the literature available at the time. The data in the literature search proved to be very scattered and insufficient to establish a well-defined growth curve and utilize rigorous forecasting techniques to estimate the technological uncertainty associated with a low TRL. Hence, *the uncertainty of achieving the expert predicted technology impact was estimated based on qualitative reasoning and mapped to a quantitative growth pattern.* The estimation was performed via a sensitivity investigation of the system metrics to a Weibull distribution. The Weibull distribution was chosen since it “is a family of distributions that can assume the properties of other distributions”[99] such as an exponential, normal, or Rayleigh. The Weibull distribution is defined by Equation 36,

where L represents the apex location of the distribution, α is a scale parameter, β is the shape parameter, and x is the random variable. Note, when β equals 3, a normal, or Gaussian, distribution is obtained. An illustration of the variation in the different Weibull parameters and the influence on the frequency distribution is provided in Figure 46. As the shape parameter β increased from 1 to 1.5 to 2, the distribution narrowed (or tightened) although the mode value shifted slightly from the location of -0.2 and the distribution shifted from an exponential to a more typical Weibull. As the scale parameter α increased from $5\%k_i$ to $30\%k_i$, the distribution widened and the mode value shifted even further to the right.

$$k_i(x)|_{T_i} = \begin{cases} \left(\frac{\beta}{\alpha}\right)\left(\frac{x-L}{\alpha}\right)^{\beta-1} \exp\left(-\left(\frac{x-L}{\alpha}\right)^{\beta}\right) & x \geq L \\ 0 & x \leq L \end{cases} \quad (36)$$

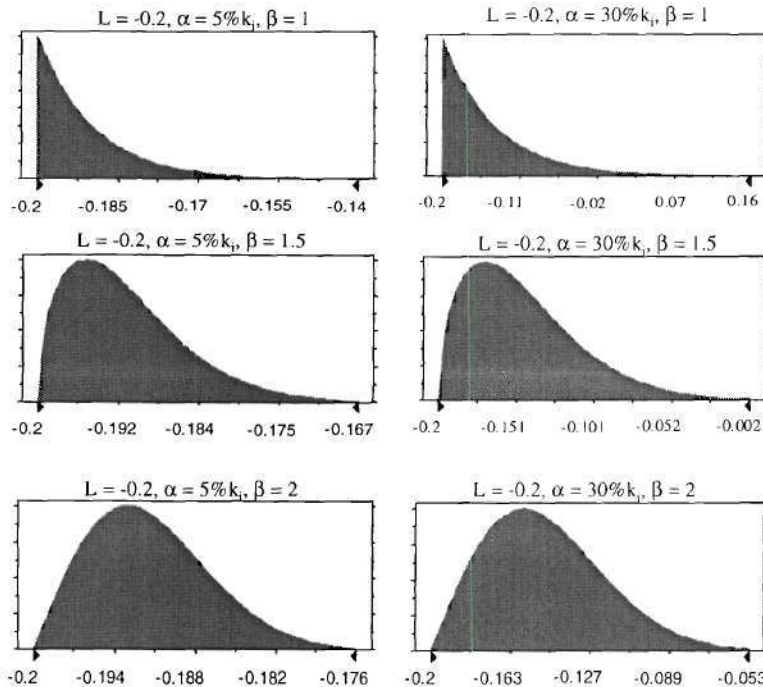


Figure 46: Visualization of Weibull Distribution Parameters

To establish the appropriate “k” factor shape distribution for a given TRL, a DoE combined with a MCS was utilized such that a metric was defined in terms of the Weibull distribution parameters. For each technology “k” vector element, $k_{i|T_i}$, in the TIM, the impact value was assumed to take the shape distribution of Equation 36. For each element, a range of applicable values for L , α , and β were defined based on the “theoretical” impact, k_i , as listed in Table XVIII. Based on these ranges, a DoE was executed for the system metrics for a given technology. For each DoE case, the “k” factors were assigned the appropriate distribution parameters and a MCS executed. For a given confidence level, the metric values were extracted and supplied to JMP[®]. Eleven DoEs were executed, corresponding to the eleven technologies, so that the sensitivity of a metric to a given technology distribution could be investigated.

Table XVIII: Range of Weibull Distribution Parameters

Parameter	Minimum	Maximum
Location, L	$\pm 5\% k_i$	k_i
Scale, α	$5\% k_i$	$50\% k_i$
Shape, β	1	2

The performance metric sensitivities due to the addition of an environmental engine (T5) and HLFC (T4) are shown in Figure 47. The “k” factors that the environmental engine influenced were: noise suppression and increased engine weight from acoustic lining and a mixer-ejector nozzle, reduced fuel flow from improved combustion efficiency, and increased RDT&E, production costs, and O&S costs. The results shown are for a 50% confidence level and are consistent for all other confidence levels. The metrics were highly sensitive to the scale parameter α , which stretched the distribution

over a larger range. Furthermore, TOGW, TOFL, and Vapp were insensitive to the variation in the “k” factor distributions, and varied less than 1% in magnitude as seen on the left. This result provided valuable insight to the significance of secondary impacts on the system. Specifically, the primary purpose of infusing the environmental engines was to reduce FON and SLN. This indeed was the impact, and there was minimal degradation to other performance metrics. The sensitivity result was consistent for the remaining technologies and metrics.

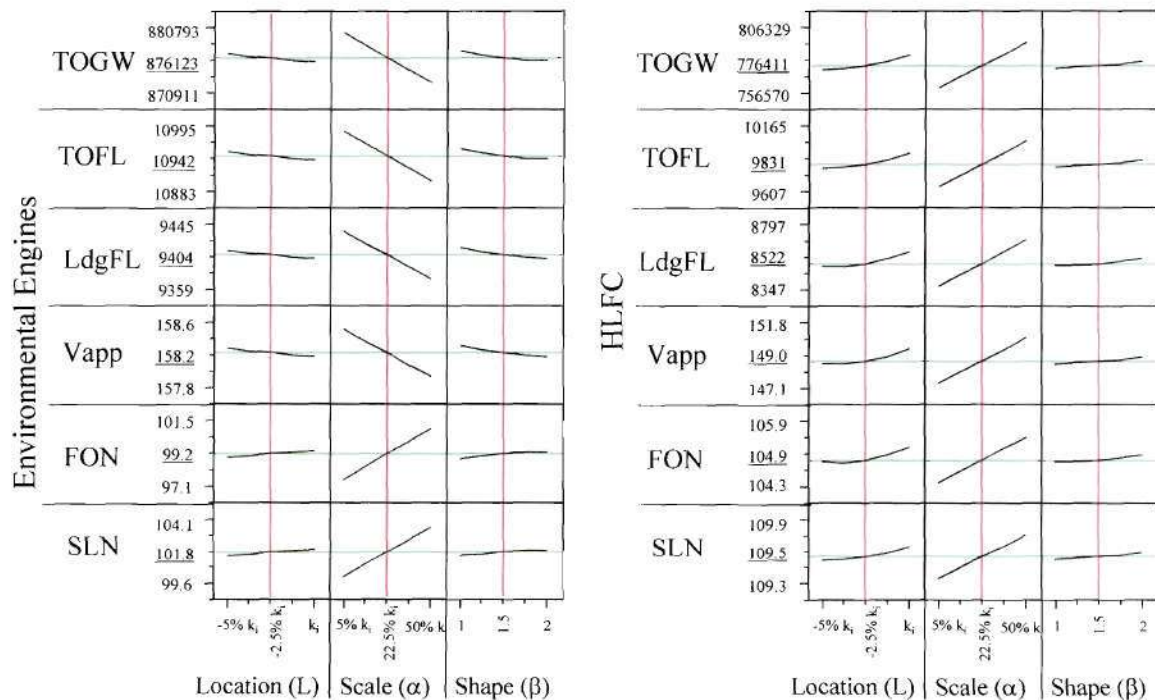


Figure 47: Metrics Sensitivity to a Weibull Distribution Variation

Based on the above sensitivity investigation, a more detailed look at the individual “k” factor element distributions ensued. The focus was to identify the Weibull distribution parameter values that could mimic the total uncertainty of the technology impact as the TRL varied. In essence, bound the uncertainty of the technology impact, as was shown in Figure 21 and Figure 22 in Chapter III, so that a quantitative evaluation

could be performed. For brevity, the investigation resulted in the location, L , defined as the “ k_i ” value from the TIM and a shape parameter β value of 2 for all technologies. The only parameter that varied was the scale parameter α and was defined as a function of TRL as in Equation 37.

$$\alpha|_{k_i, T_i, L=k_i, \beta=2} = |30\%k_i| - (TRL - 1) \frac{(|30\%k_i| - |5\%k_i|)}{8} \quad (37)$$

As a visual aid, the variation in wing weight reduction due to a composite wing is shown in Figure 48. For a composite wing (T1), the expert predicted, or “theoretical”, impact to the wing weight was a 20% reduction. This value was achieved when the TRL reached 9 since all technology developments were assumed successful. The impact was assumed deterministic at this point and represents a “theoretical” limit. Yet, at lower TRL values, the uncertainty associated with the technology was larger. As the TRL increased, the variability reduced and the mode value approached the anticipated value at a TRL of 9. This logic was used for all technology “ k ” vectors and the distribution scale parameter was defined by Equation 37 for the given technology’s TRL. The resulting shape of the distributions followed the rationale of the technology uncertainty described in Chapter III. *The definition of the “ k ” factor distribution has one critical assumption.* Regardless of the TRL, the Weibull parameters were selected such that if the “ k ” factor was a reduction from the baseline, i.e., a negative value, the resulting distribution would *never* be positive. Similarly, if a “ k ” factor increased from the baseline, i.e., a positive value, the distribution would never have negative values.

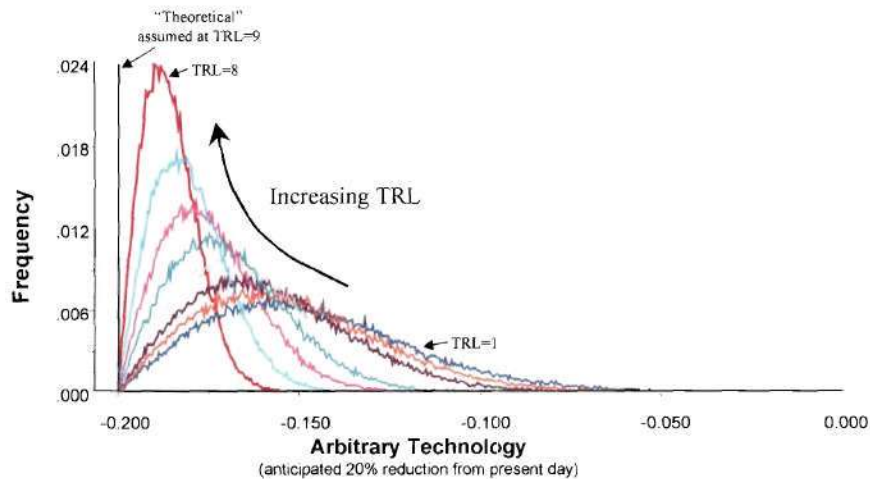


Figure 48: Example TRL “k” Factor Distribution

How does varying the TRL influence the system metrics? Consider the composite wing technology (T1), which was at a TRL of 3. The TOGW theoretical limit of T1 was 805,543 lbs. Yet, if the TRL varied between 1 and 7, as defined from Equation 37, the influence of technological uncertainty was significant as the TRL increased, as shown in Figure 49. The impact of technological uncertainty was evident with the shifting the mean (μ) and reducing the standard deviation (σ) of TOGW. For a low TRL, T1 varied between 805,543 lbs and 830,000 lbs. This variability reduced as the TRL increased and deviated over a smaller range. Thus, increasing the maturity of a technology reduced the variability on the responses and shifted the mean towards the theoretical limit. In contrast to a performance metric PDF, which shifted to a lower value, an economic metric shift was not straightforward, as shown in Figure 50. Due to the multiplicity of interactions amongst the “k” factors that reduced weight and the “k” factors that increased the economic factors, a generalized trend of increasing TRL on the economic metrics could not be established. However, this investigation provided valuable information regarding the sensitivity of a metric to variations in technological uncertainty.

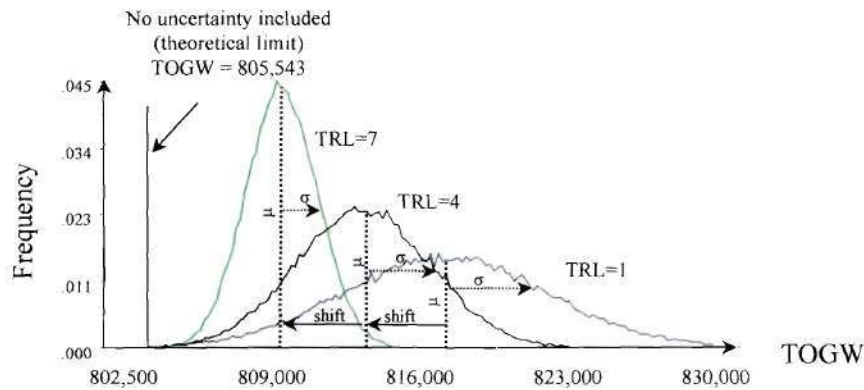


Figure 49: Influence of Increasing TRL on TOGW

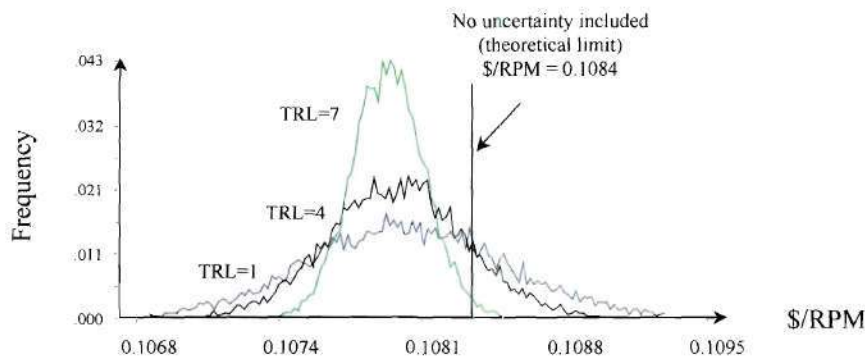


Figure 50: Influence of Increasing TRL on \$/RPM

Step 7: Technology Evaluation

The technology evaluation was performed by creating a metamodel of each system metric in Table VII as a function of the “k” vector elements. Since the technology vector of the TIM contained 16 variables, the custom-made DoE for a 16 variable RSE was used to create the second order metamodels of the metrics as a function of “k” factors. The ranges used to define the “k” factors were based on a summation of the reductions and increases from the TIM for a given “k” factor as summarized in Table XIX. The “0” implies no change in the technical metric (i.e., present day levels of technologies), while a negative denotes a reduction and a positive an increase. The assumption made in

defining the ranges was that all technologies were compatible. Although the TCM contradicts this assumption, these variable range definitions allow for changes in the anticipated technology impacts in the future. That is, once the metric RSEs were created for the ranges in Table XIX, the RSEs would still be valid and another DoE *would not* have to be regenerated if any changes occur to the technologies impacts in the TIM.

Table XIX: Bounded Nondimensional “K” Factors

Technical Metric “k” Factors Elements	Minimum (%)	Maximum (%)
Wing Weight	-35	+7
Fuselage Weight	-40	0
Engine Weight	-10	+46
Electrical Weight	0	+22
Avionics Weight	0	+21
Surface Controls Weight	-5	+10
Hydraulics Weight	-5	+5
Noise Suppression	-21	0
Subsonic Drag	-19	0
Supersonic Drag	-24	0
Subsonic Fuel Flow	-6	+3
Supersonic Fuel Flow	-6	+1
Maximum Lift Coefficient	0	+15
O&S	-2	+17
RDT&E	0	+39
Production costs	-12	+30

The resulting RSEs were visualized in JMP® to establish which “k” factors had the most significant impact on the metrics. The mapping for the 11 technologies considered is depicted in Figure 51 and Figure 52. The profiler was interpreted in the same manner described previously with a slight twist. Three important aspects of information were obtained from the prediction profilers. First, one can evaluate how much fidelity is

required in an analysis tool to model a technology. For example, if some arbitrary technology affects the hydraulics weight of the system, a lower fidelity analysis code could be used to predict the weight based on the very small prediction trace slope as seen in Figure 51. However, a higher fidelity analysis code should be used to quantify the supersonic drag to due the higher sensitivity of the metrics to this “k” factor, as shown in Figure 52. The slope of the prediction traces inform the decision-maker which “k” factor values need to be “nailed” in the analysis to minimize the influence of code fidelity to the technological uncertainty.

Also of importance from the technology mapping is the effect that degradation in technology performance would have on the system throughout the operational life. For example, an arbitrary technology was infused to suppress the noise levels and was designed for a specific noise suppression value. If the ability of that technology to suppress the noise were to degrade rapidly over the life of the vehicle, one may interpret that the noise constraints might not be met as the technology degrades due to the large sensitivity of SLN and FON metrics to noise suppression.

Finally, the prediction profilers of the technology mapping may be interpreted as a forecasting environment. For example, the SLN was a performance “show-stopper” for an HSCT concept. As is evident, a technology that suppressed the noise had the largest impact on the SLN, while the supersonic drag reduction had the largest influence on all other metrics. If one did not have specific technologies to evaluate, this mapping environment could guide the decision-maker in selecting appropriate technologies for infusion. This technique is called Technology Impact Forecasting (TIF) [41,59,92] as discussed earlier. For example, since the SLN, TOFL, LdgFL, and FON had very little if

any feasible space, the decision-maker should select a set of technologies that reduced noise, supersonic drag, wing weight, engine weight, and fuselage weight, and increased the maximum lift coefficient. These “k” factors significantly influence the metrics as seen by the large prediction trace slopes. Or, another option would be to reverse engineer the problem and determine what values of the “k” factors create a feasible configuration. This is the heart of the TIF method as was described in Chapter III for normative forecasting techniques. Thus, once the “k” factor values are established, the decision-maker must identify *specific* technologies providing the predicted values. The reverse approach was taken herein, such that specific technologies were identified for infusion, and the TIF environment was a fallout of this approach.

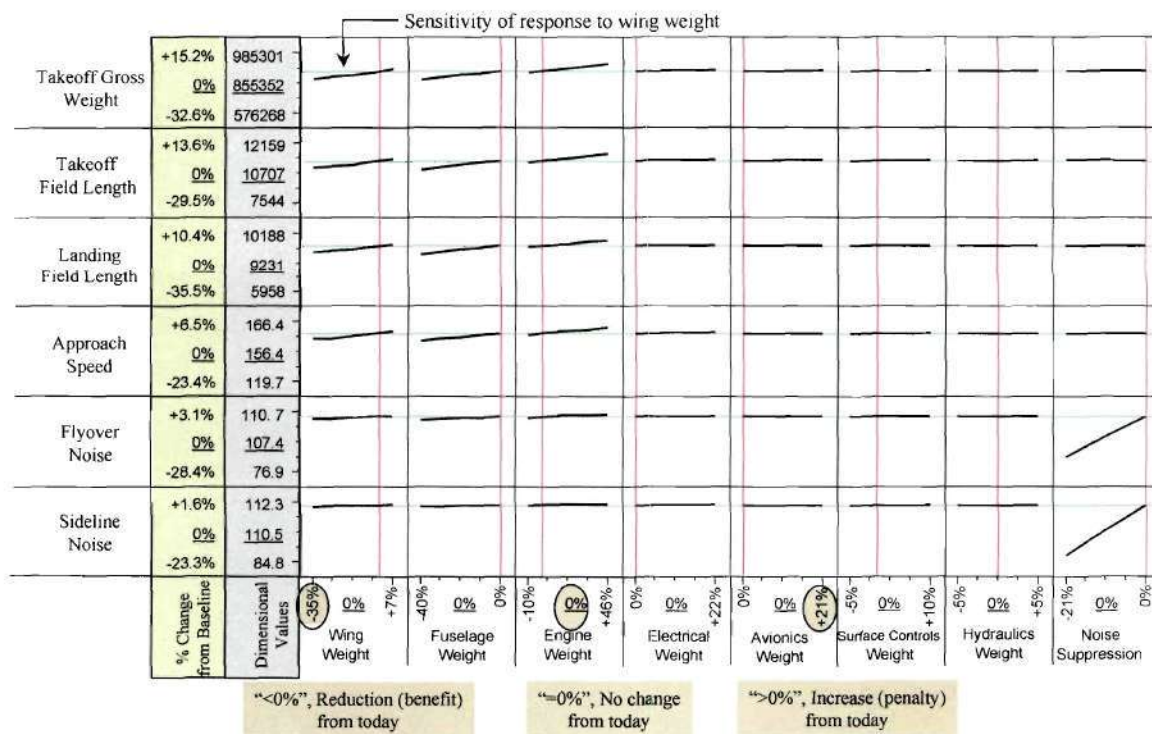


Figure 51: Visualization of the Technology Mapping (1)

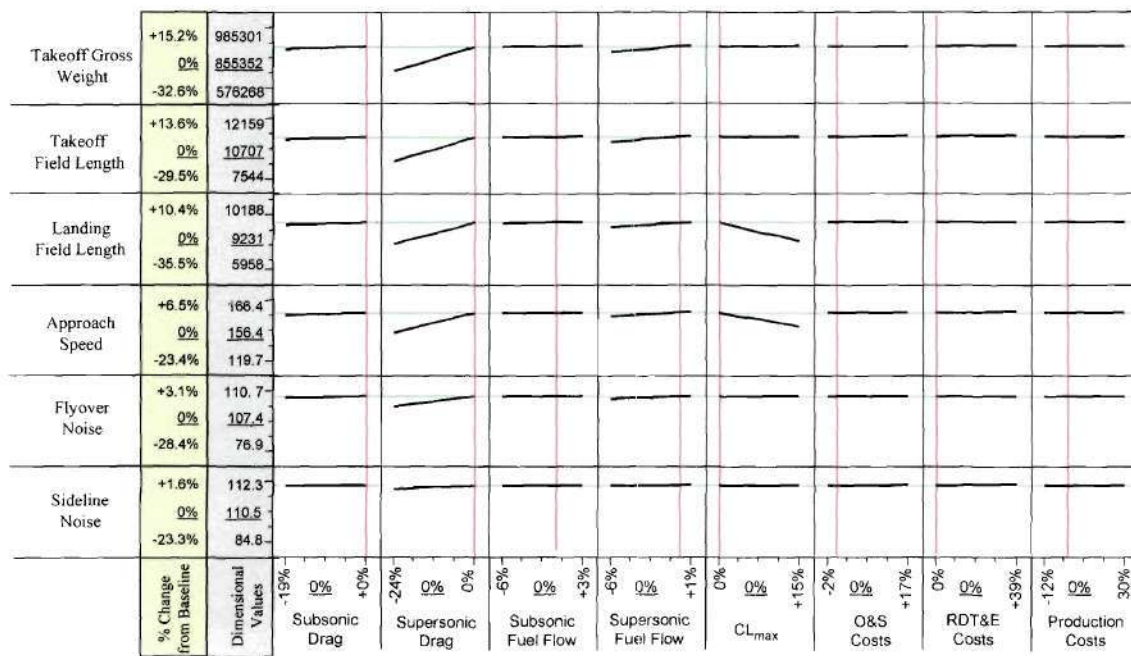


Figure 52: Visualization of the Technology Mapping (2)

Deterministic Evaluation

Once the RSEs were created for each metric, the equations were used to rapidly evaluate the technology combinations as described in Chapter III. For initial insight into the technology sensitivities, a full factorial deterministic investigation was performed. The technologies were set at the “theoretical” limit to gain a first insight. One could immediately determine which technology had the most influence on a given metric when turned “on” as shown in Figure 53. Based on the lower bound value of the metrics (e.g., TOGW=583,504 lbs or SLN=84.7 EPNLdB); a feasible solution was obtained with some combination of technologies. Recall that the SLN was the concept “show-stopper” for technical feasibility. As is evident, T5 and T11 significantly reduced the SLN when turned “on”, as indicated by the negative slope: both technologies showed promise for achieving a feasible design. However, the compatibility rules were not inherent in the

sensitivities shown. If both T5 and T11 were turned “on”, the SLN result would be meaningless, since both were competing engine technology concepts.

One should not underestimate the power of the prediction profiler in Figure 53. Once the technology environment is created, *the decision-maker can instantaneously quantify the impact that any mix of technologies has on the system under investigation; without the need to re-execute any analysis code*. Furthermore, if the anticipated impact of a technology changes as the development progresses, again, no analysis code execution is required. A simple update to the assumptions is performed and the results are obtained immediately through a simple recalculation of the RSEs.

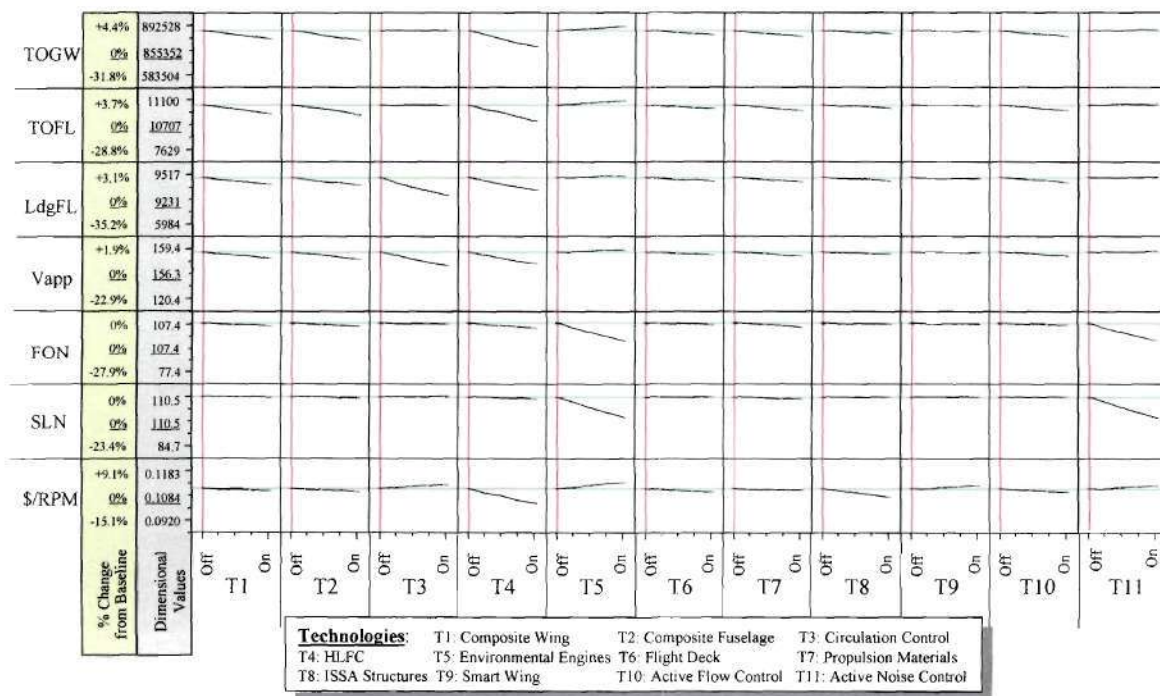


Figure 53: Full-factorial Technology Evaluation with No Uncertainty

Probabilistic Evaluation

The next step of the evaluation process was to realistically assess the impact of the technology combinations in a probabilistic sense. The appropriate Weibull distributions were assigned, as defined by Equation 37, to all technology “k” vector elements. Because the metrics were modeled as RSEs, a full factorial probabilistic investigation was pursued since the computational expense was minimal. As described previously, a MCS was executed on the 2,048 technology combinations. As an example of the results obtained, the impact of three technology combinations (T2, T2+T5, and T2+T4+T5) on the TOGW and \$/RPM is shown in Figure 54 in the form of PDFs. For the appropriate TRLs, adding technologies implied adding more uncertainty to the response and resulted in increased variability. In fact, the variability could potentially counteract any system improvements due to an increase in risk. This was evident as the addition of T5 (environmental engines) increased the variability of TOGW and \$/RPM. The primary purpose of adding T5 was to reduce the SLN (not shown), however, other metrics were degraded as seen by the shift in the distributions to higher TOGW and \$/RPM values. Furthermore, the mean of the response PDF shifted depending upon whether the technologies improved or degraded the system. If there was no influence from a given technology, the mean would not shift, but the variance may increase.

Traditional methods of evaluating the impact of technologies only look at a point estimate with no insight into the associated risks. With the approach taken herein, the risk associated with adding technologies is inherent in the process since each technology impact is modeled probabilistically. Hence, if a decision-maker desires a 90% confidence (or a 10% risk) of achieving a particular metric value, the TIES method provides the

substantiated information upon which the decision can be made with confidence. Traditional methods do not. Additionally, if one considers only performance metrics without the implications of the investment costs associated with developing a technology, one would expect that the addition of more technologies would further improve the system. From the traditional perspective of point estimates and technology benefit assessments, this is true. However, once technological uncertainty is included in the assessment, the decision as to which technologies are more effective is based on a confidence level and the associated impact at that level. For example, if the constraint value for \$/RPM was \$0.1084 in Figure 54, the confidence of achieving that value would be approximately 75% for T2, 5% for the combination of T2+T5, and 95% for T2+T4+T5. If a high confidence was desired, the decision-maker would then consider T2 or the combination of T2+T4+T5 to satisfy the \$/RPM constraint. The traditional approach to technology assessments *does not* provide this type of information.

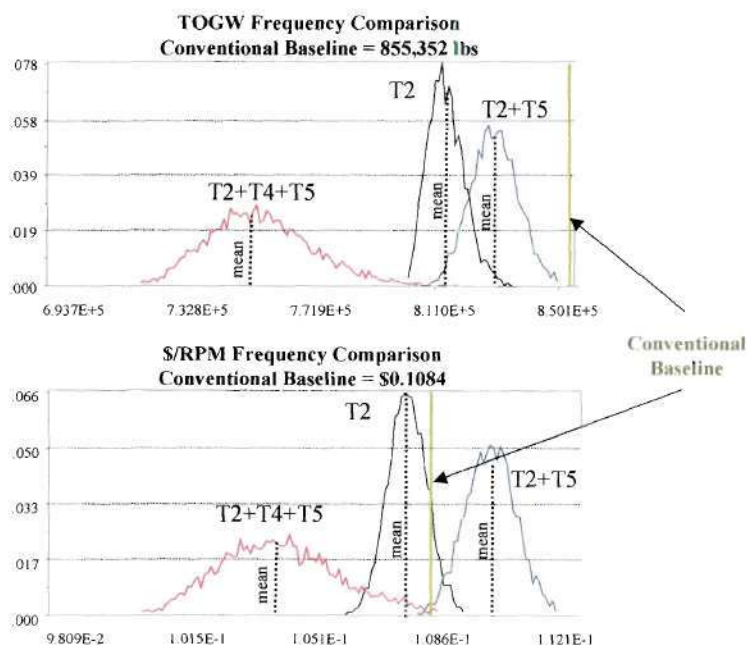


Figure 54: Impact of Immature Technologies on TOGW and \$/RPM

The full factorial probabilistic evaluation is illustrated in Figure 55 for TOGW, SLN, and \$/RPM. As discussed in Chapter III, the metric responses included the theoretical limit, R_i , the shift in the mean value of the distribution, $\Delta\mu R_i$, and the standard deviation, σR_i . From the prediction traces shown, the most influential technologies included T1, T2, T4, T5, and T11. All other technology impacts are considered moderate. The prediction traces shown are for an “on” or “off” condition, where “on” corresponds to the technology’s associated TRL as listed in Table XVII. The variability in the metrics, σ , was due to the uncertainty in the “k” factors for which the technology affects as described previously.

The prediction profiler is interpreted as follows. If one were to select a mix of T4 and T5, the hairlines would be moved to the “on” position. Then, the metric value, say TOGW, would be read off the ordinate as 781,827 lbs, and add the $\Delta\mu$ of TOGW due to T4 and T5 of 14,830 lbs to that value to get the mean of the TOGW PDF of 796,657 lbs with a standard deviation of 12,470 lbs. If one assumes a normal distribution, the impact of the uncertainty associated with infusing T4 and T5 was defined with a mean of 796,657 lbs and a standard deviation of 12,470 lbs. The normal distribution parameters could be evaluated for any technology combination in the same manner.

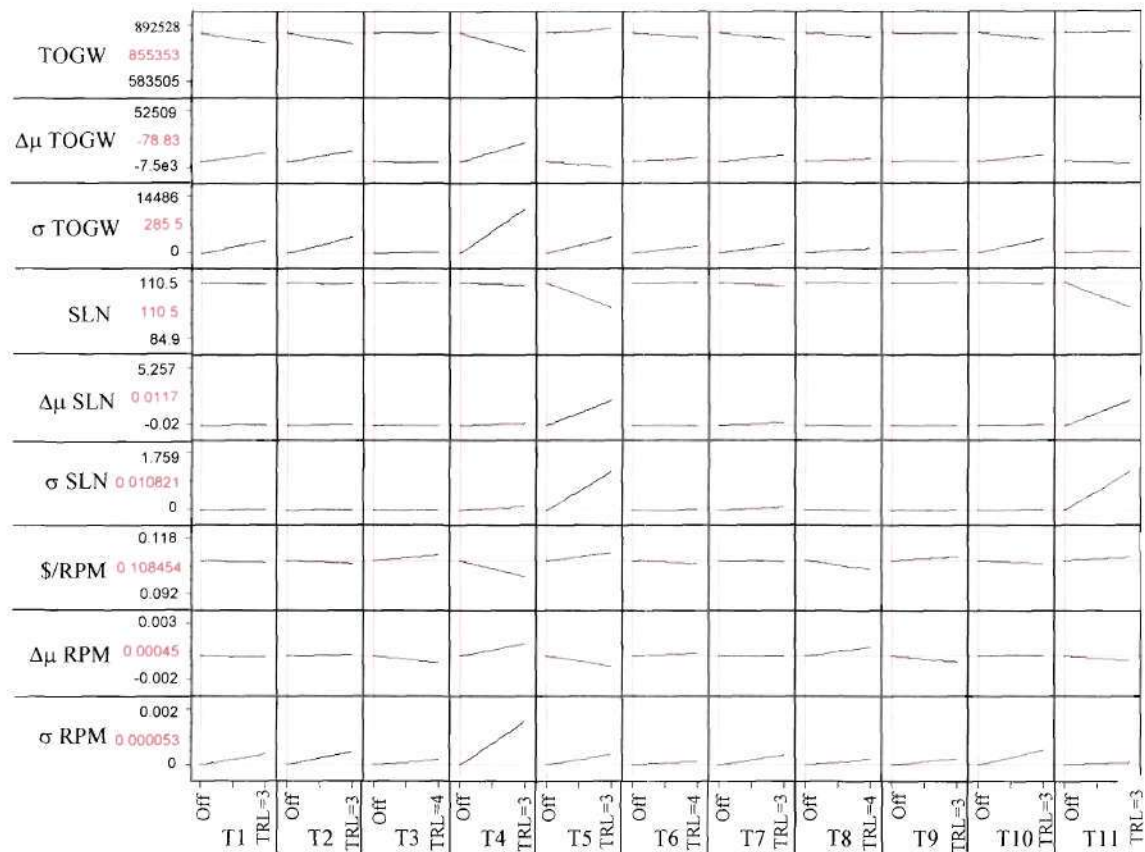


Figure 55: Full-factorial Probabilistic Evaluation

Confirmation of Assumed Response Distribution Shapes

The metric PDFs that resulted from the evaluation step were assumed as normally distributed. This assumption was made from an investigation performed on a randomly selected set of technology combination PDFs. For example, consider the impact of T1 on SLN and TOGW. If one were to fit a distribution to the TOGW PDF result, a Gamma distribution was the most appropriate approximation, as illustrated on the left of Figure 56 and Figure 57. The error associated with a Gamma fit was fairly random across the sampled data as shown on the bottom left. If a normal distribution was fit to the same sample data, as shown on the right of both figures, the error with the approximation

increased around the mode value of the data and had a discernible pattern. The original data mode value was, to some extent, skewed to the left with maximum error larger than the Gamma approximation. Recall in Figure 54, the PDF of the combination of three technologies, T2+T4+T5, approached a normal distribution with minimal error. Hence, the assumption was made that the metric PDFs were normally distributed and were defined by a mean, μ , and a standard deviation, σ . This assumption was further justified since the likelihood of a single technology creating a feasible space was small. Thus, using more technologies implied more input distributions, which implied a more normally distributed metric PDF by the Central Limit Theorem. With the assumption of a normal distribution, all the techniques for Gaussian distribution manipulations hold true. The confirmation of the assumed metric distributions was another means of validating the TIES method.

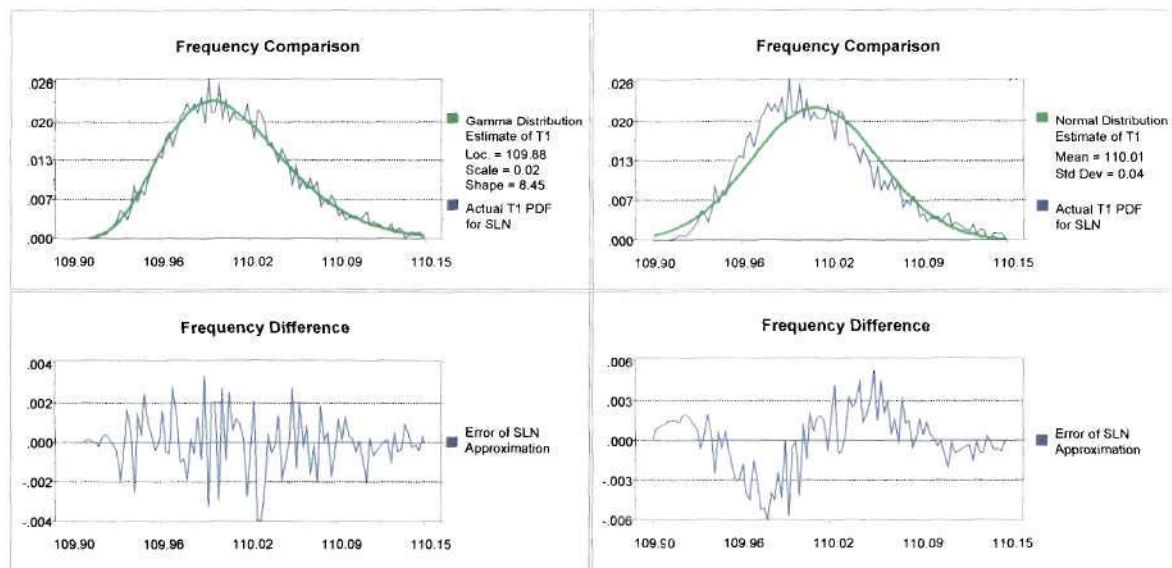


Figure 56: Validation of Response Distribution Shapes for SLN

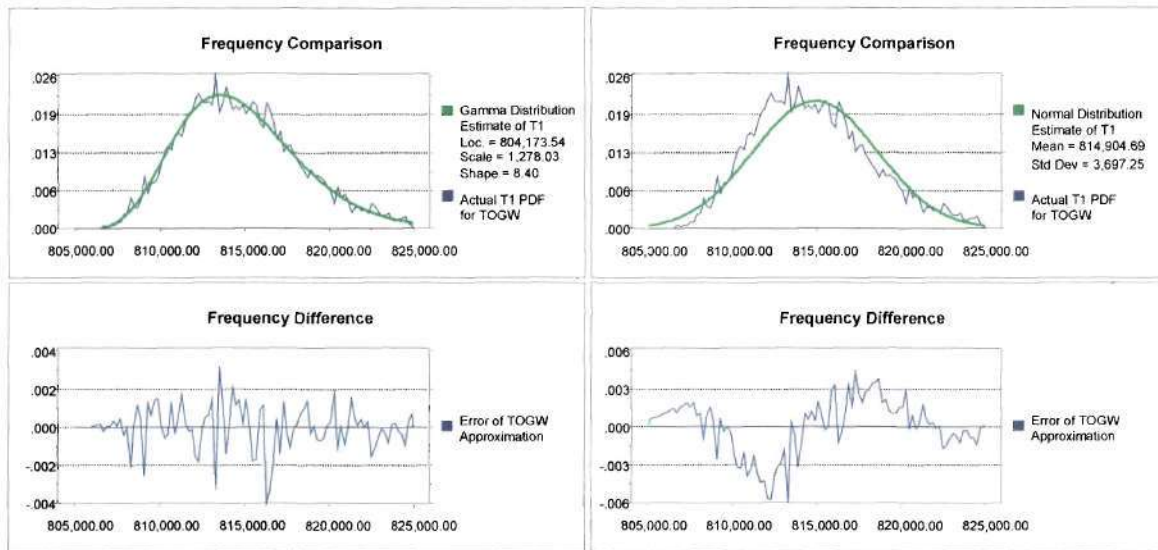


Figure 57: Validation of Response Distribution Shapes for TOGW

Population of Decision Matrix

For the purpose of technology selection, four Decision Matrices (DM) were populated with deterministic metric values for each compatible alternative. One consisted of the deterministic “theoretical” values, and the remaining three were populated by extracting the 10%, 50%, and 90% confidence levels from each alternative metric CDF. Each matrix was 272 by 11, where 272 represented the number of compatible alternatives and 11 the number of system metrics.

Step 8: Technology Selection

The final step in TIES was to determine the “best” family of technology alternatives whereby customer satisfaction could be achieved and maximized. The best alternatives were established from a balancing of the three suggested selection techniques: MADM, technology frontiers, and resource allocation. The result of each approach is described below.

MADM: TOPSIS

The TOPSIS technique was applied on all four DM to identify the best mix of technologies. Each metric was classified as a “cost” since minimization was desired. Various weighting scenarios were considered in the ranking process, and ranged from heavy performance to relatively evenly distributed, as listed in Table XX. This approach simulated the subjectivity of the decision-maker. TOPSIS was executed for each DM and each weighting scenario.

Table XX: TOPSIS Weighting Scenarios

Metric	Preference Weighting Scenario									
	Heavy Performance							Evenly Distributed		
	1	2	3	4	5	6	7	8	9	10
TOGW	0.1	0.15	0.2	0.15	0.2	0.2	0.05	0.05	0.05	0.1
TOFL	0.1	0.1	0.1	0.15	0.1	0.1	0.05	0.1	0.1	0.1
LdgFL	0.05	0	0.05	0	0.05	0.05	0.05	0.05	0.05	0.05
Vapp	0.15	0.15	0.05	0.15	0.05	0.05	0.05	0.05	0.05	0.1
FON	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1
SLN	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1
Acq\$	0.1	0.05	0.1	0.05	0.1	0.1	0.1	0.1	0.1	0.1
RDT&E	0	0	0.1	0	0.1	0.1	0.1	0.1	0.1	0.1
\$/RPM	0	0	0	0	0	0	0.1	0	0.1	0.05
TAROC	0	0.05	0	0.1	0.1	0	0.1	0.1	0	0.1
DOC+I	0	0	0	0	0	0	0	0.05	0.05	0.1

Some interesting results were obtained from applying TOPSIS. First, the top 15 of the 272 technology combinations were compared for each DM and weighting scenario. The same 7 combinations ranked in the top 15 regardless of the weighting scenario or confidence level considered. Although the absolute ranking order and closeness to the ideal solution varied, the same technology mixes appeared. The 7 dominant mixes are

listed in Table XXI. At first, this result would suggest that a probabilistic assessment might not be needed when evaluating the impact of immature technologies. Upon further investigation, this was an erroneous conclusion. Consider the TOPSIS results for weighting scenarios #1 and #9 for the 7 technology mixes. The closeness value and resulting TOPSIS ranking for each of the 7 mixes are listed in Table XXII and Table XXIII for the two weighting scenarios. Three concepts appeared superior regardless of the weighting scenario and include concept number 1369, 1489, and 1497. Each of these concepts had a least five technologies and ranked in the top five regardless of which metric was preferred. However, concepts 505 and 1481 were highly ranked for heavier performance weighting and 377 and 1361 were for heavier economic weightings. Next, additional insight was gained from the different weighting scenarios in the form of the recurring technologies. In particular, T2, T4, and T6 occurred in 6 of the top alternatives and suggests that these technologies provided significant benefit with minimal penalty the system.

Table XXI: Dominant Technology Mixes

Concept Number from Full Factorial	Technology Mix	Scenarios that Concept Ranked
377	T2+T4+T5+T6+T7	Economic
505	T2+T3+T4+T5+T6+T7	Performance
1361	T2+T4+T6+T11	Economic
1369	T2+T4+T6+T7+T11	ALL
1481	T2+T3+T4+T7+T11	Performance
1489	T2+T3+T4+T6+T11	ALL
1497	T2+T3+T4+T6+T7+T11	ALL

Table XXII: TOPSIS Results for Top Mixes of Weighting Scenario #1

Concept Number	<u>"Theoretical"</u> Closeness (Rank)	<u>10% Confidence</u> Closeness (Rank)	<u>50% Confidence</u> Closeness (Rank)	<u>90% Confidence</u> Closeness (Rank)
377	0.7768 (10)	0.7737 (11)	0.7529 (13)	0.7226 (13)
505	0.8062 (3)	0.7997 (6)	0.7762 (6)	0.7448 (8)
1361	0.7774 (9)	0.7845 (9)	0.7686 (7)	0.7411 (9)
1369	0.8018 (4)	0.8415 (4)	0.7975 (3)	0.7720 (3)
1481	0.7981 (5)	0.8145 (3)	0.7927 (4)	0.7632 (5)
1489	0.8231 (2)	0.8385 (2)	0.8170 (2)	0.7865 (2)
1497	0.8279 (1)	0.8449 (1)	0.8231 (1)	0.7942 (1)

Table XXIII: TOPSIS Results for Top Mixes of Weighting Scenario #9

Concept Number	<u>"Theoretical"</u> Closeness (Rank)	<u>10% Confidence</u> Closeness (Rank)	<u>50% Confidence</u> Closeness (Rank)	<u>90% Confidence</u> Closeness (Rank)
377	0.7651 (5)	0.7619 (5)	0.7379 (6)	0.7050 (8)
505	0.7530 (8)	0.7473 (10)	0.7206 (14)	0.6848 (15)
1361	0.7936 (1)	0.8066 (2)	0.7886 (1)	0.7610 (1)
1369	0.7910 (2)	0.8078 (1)	0.7862 (2)	0.7568 (2)
1481	0.7318 (13)	0.7486 (9)	0.7232 (12)	0.6898 (13)
1489	0.7865 (3)	0.8047 (3)	0.7799 (3)	0.7463 (3)
1497	0.7763 (4)	0.7944 (4)	0.7683 (4)	0.7344 (4)

However, one of the deficiencies of TOPSIS, and MADM techniques in general, was the non-intuitive numerical result. This was the case with the closeness values listed in Table XXII and Table XXIII. How do these 7 combinations perform in relation to the SLN and the \$/RPM metrics? These CDFs are shown in Figure 58 and Figure 59, respectively, for the 7 dominant technology mixes. All 7 technology concepts could meet

the SLN constraint of 103 EPNLdB with at least a 95% confidence. However, only 5 of the 7 concepts could meet the \$/RPM constraint of \$0.10. Concepts 505 and 1481 could not, thus the low rankings in scenario #9. A major limitation of TOPSIS was discovered through this investigation. Although a technology combination may rank high amongst a finite set of alternatives, the TOPSIS technique *does not* inform the decision-maker whether or not a given alternative *actually* satisfies the metric constraint values. This was the case with concepts 505 and 1481 with respect to \$/RPM. One solution to this dilemma would be to screen out any alternatives that do not meet the constrained metrics prior to applying TOPSIS, since the technique is only a product selection technique. Thus, the results would not be biased towards solutions that cannot satisfy rigid constraints.

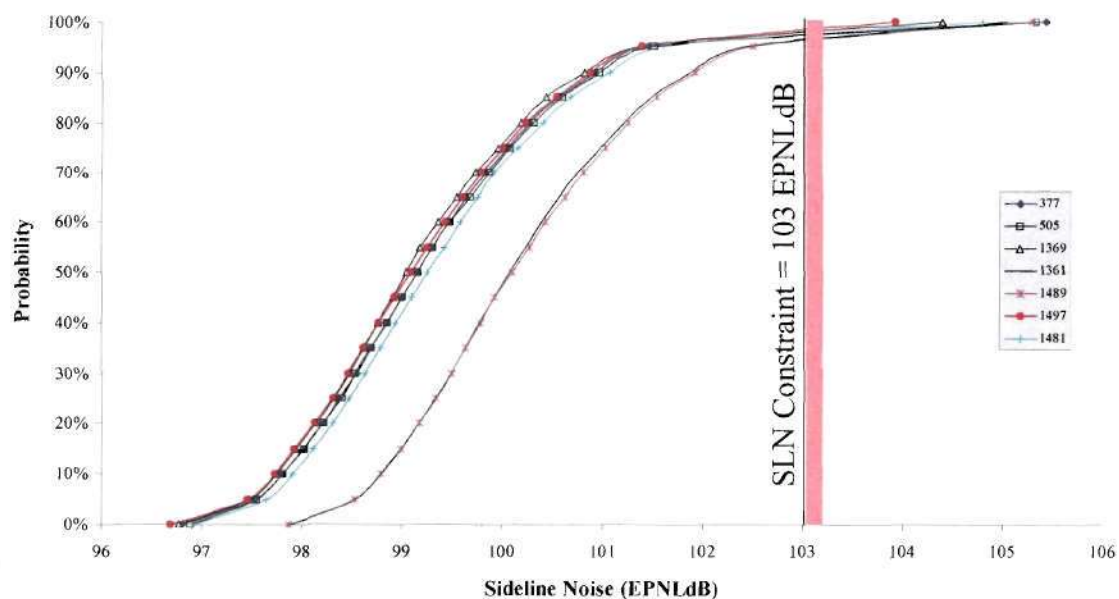


Figure 58: TOPSIS Top Performers for SLN

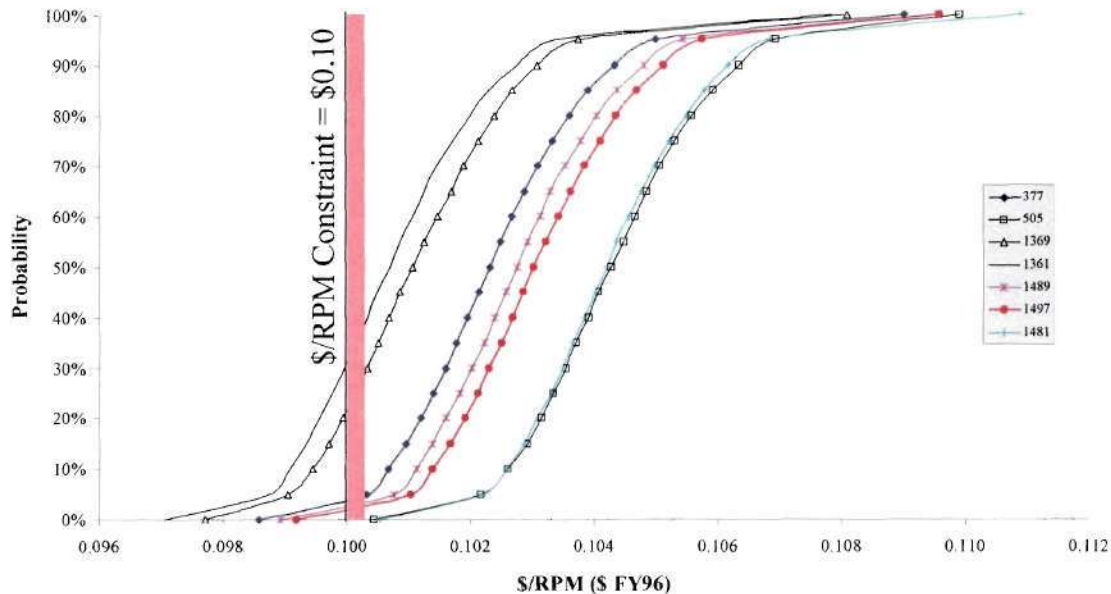


Figure 59: TOPSIS Top Performers for \$/RPM

Finally, TOPSIS did not discriminate as to the number of technologies that were infused to the vehicle. Of the top 7 performers, the least amount of technologies infused was 4 in concept 1361, which contained T2, T4, T6, and T11. In a realistic design program, it is highly unlikely that a company could pursue the development of more than a few immature technologies. Thus, the identified deficiencies of TOPSIS, as the only means by which alternatives are selected, supported the need for additional selecting techniques.

Technology Frontiers

The technology frontier technique was applied to the four DMs (“theoretical” and 10%, 50%, and 90% confidence levels). The performance effectiveness parameter, PE, was defined as a function of TOGW, TOFL, LdgFL, Vapp, FON, and SLN, and the economic effectiveness parameter, EE, was defined using Acq\$ and \$/RPM. The

economic measure of comparison was chosen to be the RDT&E costs associated with a given technology combination. *RDT&E was chosen as a representative economic parameter since, at present, a capability to predict the investment costs associated with the development of an immature technology does not exist.* All metrics contributing to the Effectiveness Parameters were classified as “costs” since minimization was desired.

However, the original definition of the Effectiveness Parameters was modified from the description provided in Chapter III to account for any metric constraint violations. This course of action was a direct consequence of the results obtained from the MADM approach. Originally, the frontiers were calculated without this logic, and the family of technology alternatives that resulted could not meet all metric constraints. Thus, those results are not shown for brevity, and the modified version of the frontiers is presented.

From the original set of 272 compatible technology alternatives, feasibility logic was applied. Each alternative performance and economic metric was compared to the constraint value. If any metric could not meet the target, the alternative was deemed “compatible, but not feasible”. This rationale was applied to each DM and resulted in *compatible and feasible* alternatives. Subsequently, a simplified additive weighting utility function was used to represent the Effectiveness Parameters. The PE was defined as:

$$PE_{Alt_i} = \frac{1}{6} \frac{TOGW_{BL}}{TOGW_{Alt_i}} + \frac{1}{6} \frac{TOFL_{BL}}{TOFL_{Alt_i}} + \frac{1}{6} \frac{LDGFL_{BL}}{LDGFL_{Alt_i}} + \frac{1}{6} \frac{Vapp_{BL}}{Vapp_{Alt_i}} + \frac{1}{6} \frac{FON_{BL}}{FON_{Alt_i}} + \frac{1}{6} \frac{SLN_{BL}}{SLN_{Alt_i}} \quad (38)$$

Similarly, the EE was defined as

$$EE_{Alt_i} = \frac{1}{4} \frac{Acq\$_{BL}}{Acq\$_{Alt_i}} + \frac{3}{4} \frac{\$/RPM_{BL}}{\$/RPM_{Alt_i}} \quad (39)$$

The PE was equally weighted since, by definition, the concepts that did not meet the imposed constraints were screened out and each metric was of equal importance. However, the EE was weighted more heavily towards \$/RPM, since the Acq\$ was an artificial constraint imposed for discussion purposes. The PE and EE thresholds were defined with the same weighting preference as defined in Equation 40 and Equation 41. Artificial constraints were imposed on TOGW (750,000lbs) and Acq\$ (\$185M) which resulted in a $PE_{threshold}$ of 1.0392, $EE_{threshold}$ of 1.0644, and $SE_{threshold}$ of 1.0518.

$$PE_{threshold} = \frac{1}{6} \frac{TOGW_{BL}}{750,000} + \frac{1}{6} \frac{TOFL_{BL}}{11,000} + \frac{1}{6} \frac{LdgFL_{BL}}{11,000} + \frac{1}{6} \frac{Vapp_{BL}}{155} + \frac{1}{6} \frac{FON_{BL}}{106} + \frac{1}{6} \frac{SLN_{BL}}{103} \quad (40)$$

$$EE_{threshold} = \frac{1}{4} \frac{Acq\$_{BL}}{185} + \frac{3}{4} \frac{\$/RPM_{BL}}{0.1} \quad (41)$$

Based on the inefficiency of TOPSIS to disregard non-feasible technology combinations in the selection process, the original set of 272 compatible technology combinations was reduced with a logical statement that dismissed any concept that could not meet any of the imposed performance constraints. For example, consider the PE theoretical limit for the entire technology space of 2,048 technology alternatives in Figure 60. With the feasibility logic applied, the technology space contains three classifications: incompatible, compatible and not feasible, and compatible and feasible.

The PE for the incompatible cases were included to depict the reduction in the technology space once the compatibility logic was applied. None of the alternatives had a PE value less than 1, which was indicative of the baseline value. Although a given set of

technologies may, in fact, degrade some performance metrics, the benefit supplied to other performance metrics outweighed any degradation. With the feasibility logic applied to the remaining compatible alternatives, two observations were made. If the frontiers were applied to all the compatible cases, including ones not feasible, the “ideal” solution would be meaningless since the minimum RDT&E that would define the solution would have resulted from a non-feasible alternative. Thus, the “best” compromise solution would also be meaningless since it based on an “ideal” solution created by a non-feasible alternative. Second, with the feasibility logic applied, all remaining alternatives surpassed the $PE_{\text{threshold}}$ and the determination of the “best” compromise was a straightforward product selection of a feasible alternative. However, the compatible and feasible technology space had a higher range of RDT&E costs and implied that feasibility was achieved, but at a cost.

The “theoretical” limit of EE for the entire technology space is shown in Figure 61. The notion of feasibility at a cost is clearly evident from this perspective. The incompatible frontier had a good number of alternatives that could meet the $EE_{\text{threshold}}$. However, once compatibility and then feasibility rules were applied, only three alternatives could satisfy the threshold value for the “theoretical” limit.

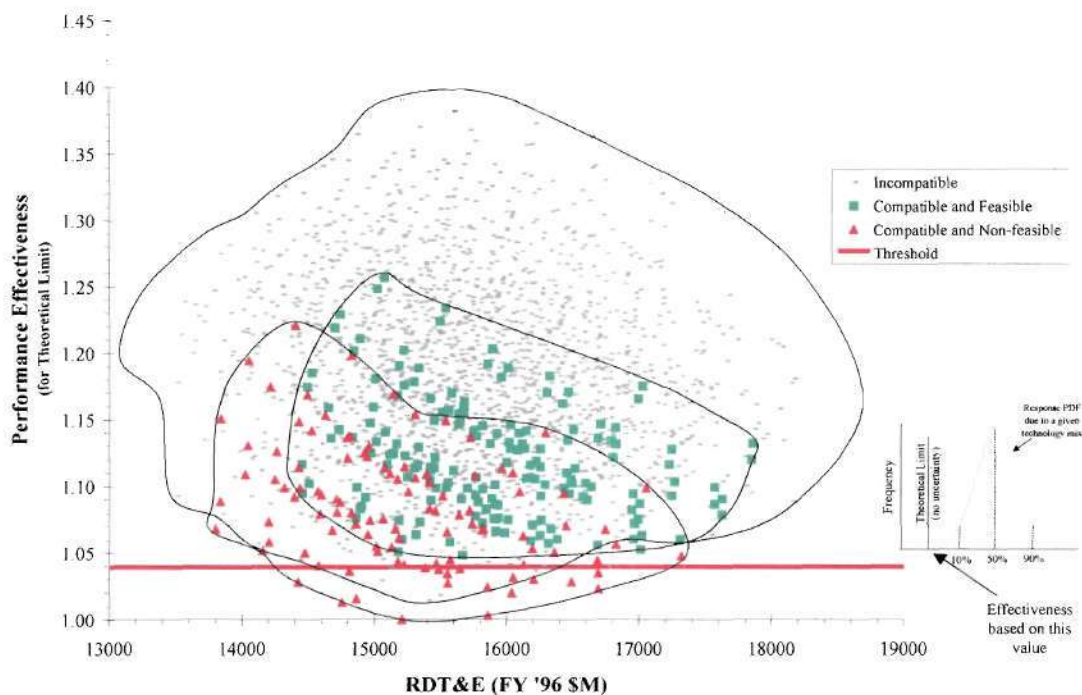


Figure 60: Entire Technology Space PE with NO Uncertainty (Theoretical Limit)

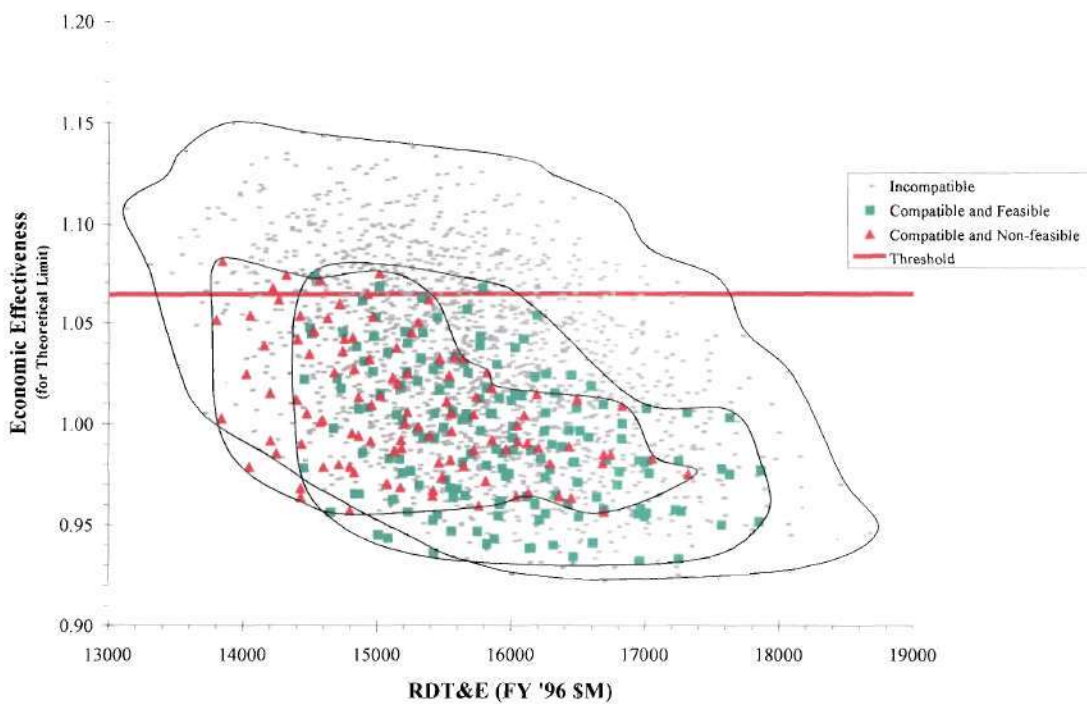


Figure 61: Entire Technology Space EE with NO Uncertainty (Theoretical Limit)

Performance Effectiveness Frontier

Based on the compatible and feasible discussion, the original set of 272 alternatives in each DM was reduced. The number of alternatives that resulted for the “theoretical” limit was 166, the 10% confidence was 168, the 50% confidence was 164, and the 90% confidence was 131, and indicated that as the confidence level increased, some feasible alternatives could not meet the constraints. Of the compatible and feasible alternatives, the maximum number of technologies infused was 6 and a minimum of 2. The PE for the “theoretical” technology impact is depicted in Figure 62. The alternatives were grouped by how many technologies were contained within the alternative, i.e., 2 to 6 technologies, and plotted with the associated RDT&E costs. The minimum value of RDT&E (\$14,451M) and the maximum value of PE (1.2567) determined the “ideal” solution.

A few interesting results were obtained from the technology frontier that did not include uncertainty. First, clusters of alternatives were evident that shared the same number of technologies. All of the combinations that had 2 technologies were clustered at low PE values and had a moderate range of RDT&E. The group cluster increased in PE and varied over a larger range of RDT&E as the number of technologies increased. This trend was also evident with the combinations that had 5 technologies. This result was anticipated since the addition of more technologies should increase the benefit to the system. Yet with these larger technology combinations, the influence of increased development cost was not evident, since some combinations had very high PE values and lower RDT&E costs. This result was explained by the dependency of RDT&E on component and system weight. The weight dependency is inherent in any non-activity-based cost estimating analysis. For these cases, although the relative RDT&E costs was

increased through a complexity factor for the different technologies, the increase was countered by a significant reduction in weight, and as a result, the absolute value of RDT&E reduced. Thus, the decision-maker should take care in selecting the measures by which EPs are compared. The compromised solution from the “ideal” contained 5 technologies: T2+T3+T4+T6+T11.

The next comparison was the PE with technological uncertainty. The 50% confidence level is shown in Figure 63. The introduction of uncertainty reduced the “ideal” solution from the theoretical limit PE value of 1.2567 to 1.1986 and increased the RDT&E from \$14,451M to \$14,621M. The entire technology space had a reduction in absolute PE and increase in RDT&E. The “best” compromise solution remained the combination of T2+T3+T4+T6+T11.

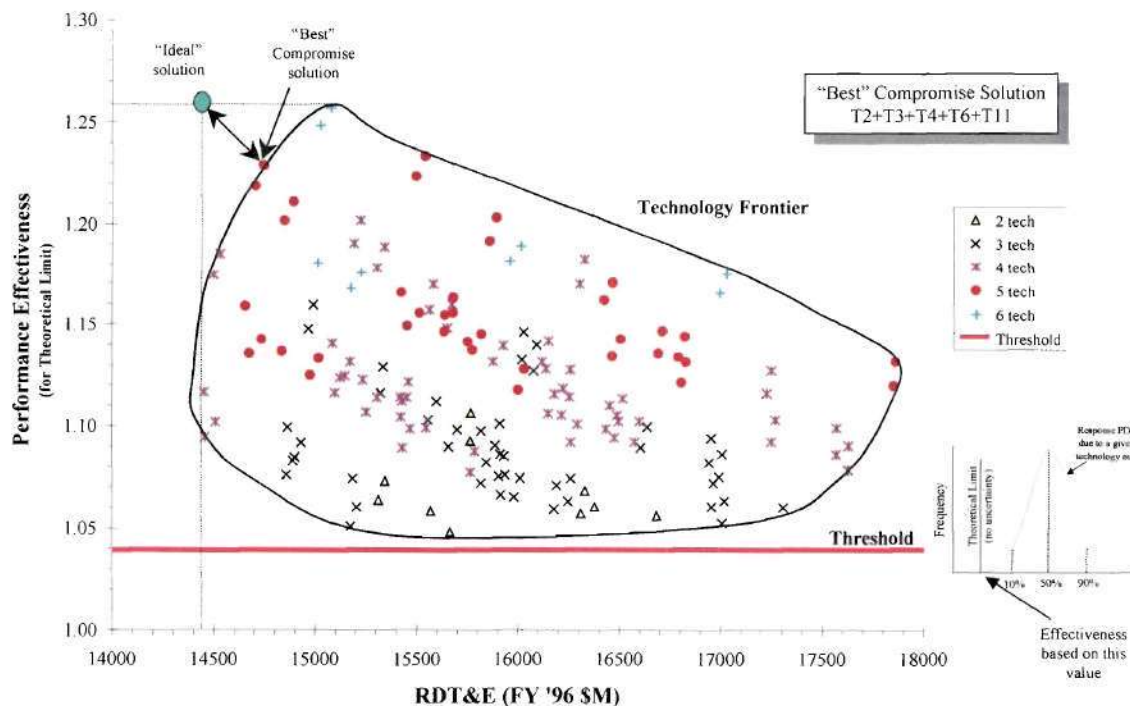


Figure 62: Performance Effectiveness with NO Uncertainty (Theoretical Limit)

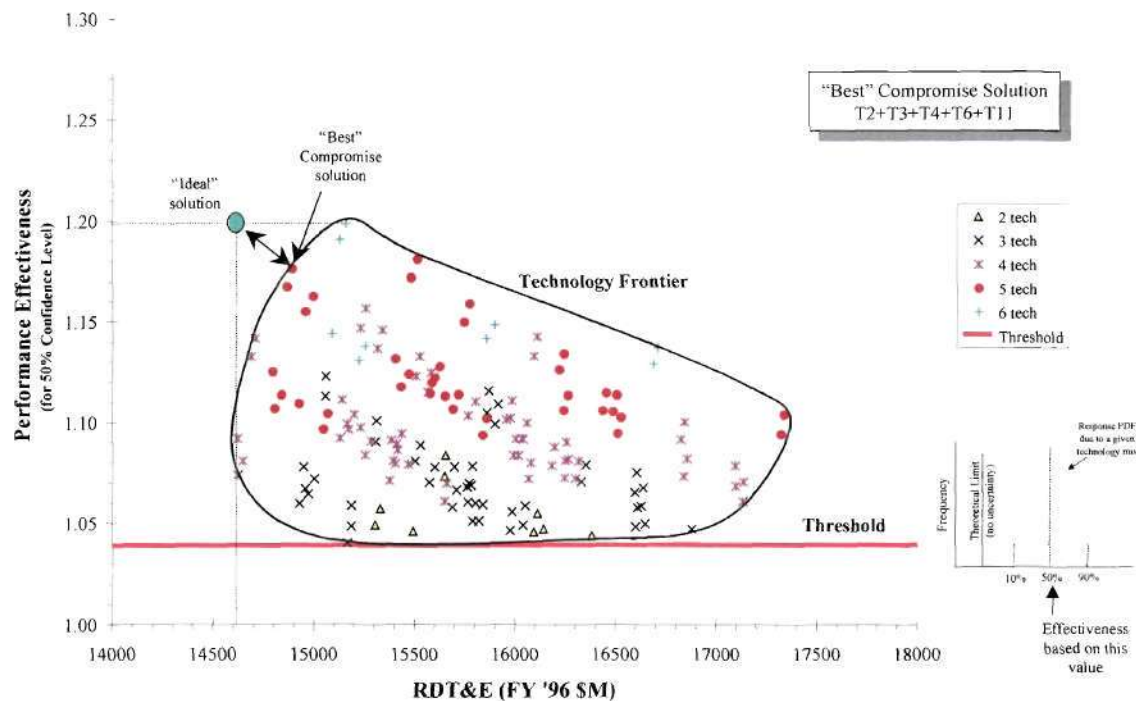


Figure 63: Performance Effectiveness with Uncertainty

As a final PE comparison, each technology frontier was compared to provide insight as to the influence of uncertainty to the technology space as shown in Figure 64. The "theoretical" limit frontier provided the highest PE value, thus the highest "ideal" solution. As the confidence level increased, or conversely as the risk was reduced, the "ideal" solution reduced in PE and increased in RDT&E. The "best" compromise solution followed suit and contained the combination of T2+T3+T4+T6+T11 for all confidence levels. At low values of PE, the bottom portion of the frontiers had little variation in PE due to the fact that the technology combinations that defined the lower curve contained only 2 or 3 technologies. Thus, the amount of technological uncertainty introduced to the PE was small and the variability in the performance metrics followed the same trend. In contrast, the upper portion of each frontier had a large variability since 5 or more technology combinations established that portion of the frontiers. The larger

PE variability was due to more technological uncertainty as was discussed in Step 7 with the impact of an increasing number of immature technologies on the metrics. However, the associated variability in RDT&E at any point on the frontiers was substantial as shown by the shifting of the frontiers to higher RDT&E values at higher confidence levels.

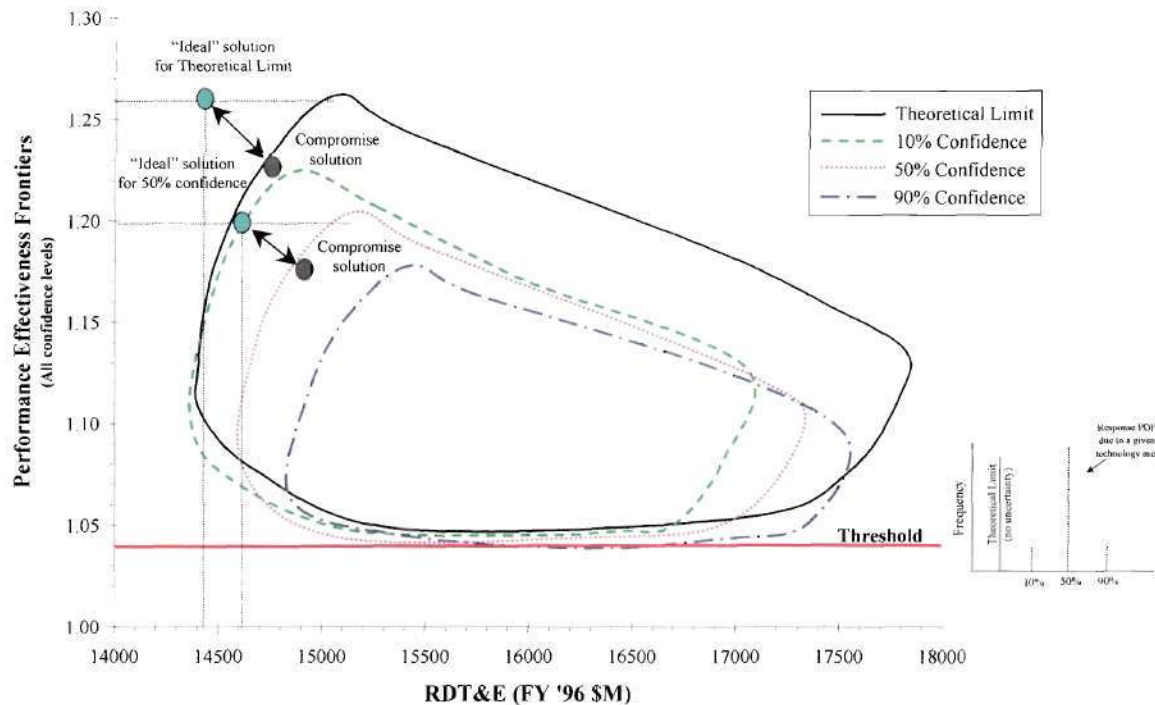


Figure 64: Comparison of Performance Effectiveness at Different Confidence Levels

Economic Effectiveness Frontier

Next, the economic effectiveness (EE) parameter was investigated. For initial insight, the “theoretical” limit frontier was considered and shown in Figure 65. The threshold was defined with a target value of \$0.1 for \$/RPM and \$185M for the acquisition price (Acq\$). The acquisition price value was established to be competitive with existing large subsonic transports with which the HSCT would compete. Thus, the

EE threshold was 1.0644 for this value of Acq\$. The impact of this limit on the number of economically viable solutions was obvious. Only three combinations surpassed the threshold and included T2+T4+T6+T11, T2+T6+T8+T10+T11, and T6+T8+T10+T11. Three viable combinations provided very little design freedom. At this point the decision-maker could either increase the target value for Acq\$ from \$185M to \$200M to reduce the threshold limit to 1.0456. This trade-off would increase the number of viable solutions for the economic effectiveness. Otherwise, if the Acq\$ was a rigid criteria that could not be negotiated, the 3 alternatives that exceeded the threshold *must be chosen*, although 2 were not the “best compromise solutions” and had a higher RDT&E cost.

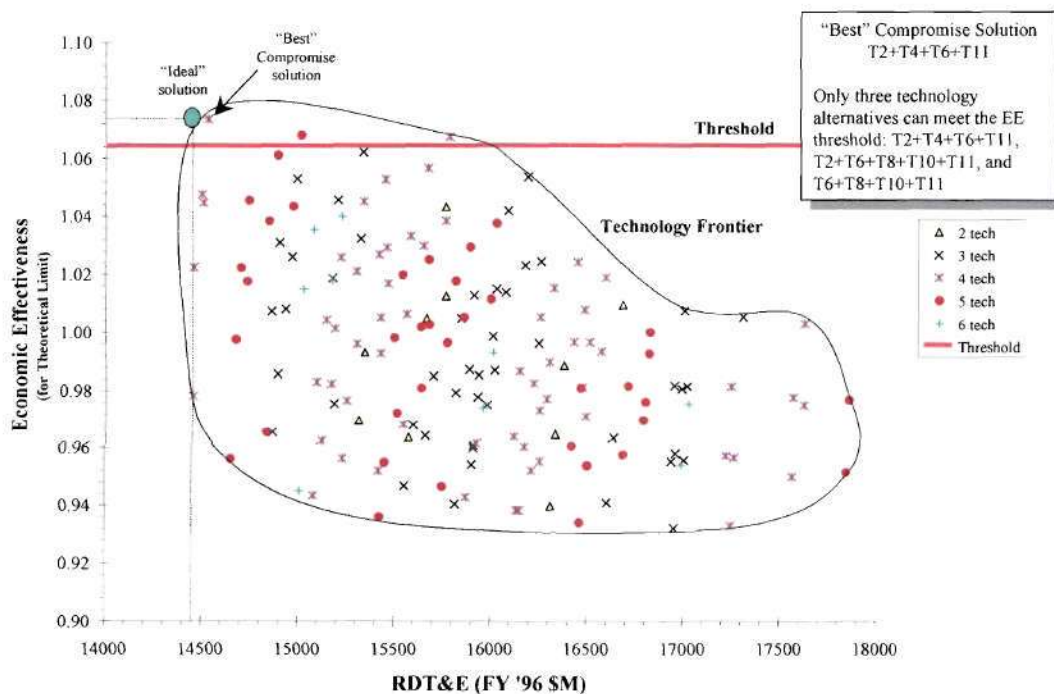


Figure 65: Economic Effectiveness with NO Uncertainty (Theoretical Limit)

The “compromised” solution, T2+T4+T6+T11 was extremely close to the “ideal” solution. Unlike the PE, the grouping of the number of technologies was more scattered rather than clustered. Furthermore, the EE values for approximately half of the

combinations reduced the EE from the baseline value of 1 due to the increased RDT&E, production, and O&S penalties imposed by most technologies considered. The alternatives that improved the EE were ones in which significant improvements in the PE were achieved, such that the cost penalties were countered. The “best” compromise solution from the PE frontiers (T2+T3+T4+T6+T11) had a corresponding EE value of 1.0456, which was significantly lower than the threshold limit.

At the 50% confidence level, if the Acq\$ target value was rigid at \$185M, all compatible and feasible alternatives fell below the EE threshold, as seen in Figure 66. The compromised solution remained the same as in the “theoretical” case with a combination of T2+T4+T6+T11. The technological uncertainty condensed the frontier space and reduced the “ideal” solution from an EE value of 1.0735 to 1.0557 and increased the RDT&E as in the PE investigation. Again, the decision-maker must make a trade-off as to which technology combination to select.

The four EE frontiers were evaluated to establish the influence of technological uncertainty and compared to the trends obtained for the PE as shown in Figure 67. The “ideal” solution reduced and fell below the acceptable threshold for confidence levels greater than 10%. Unlike the convergence of the PE frontiers at low values of PE, the EE frontiers varied for all confidence levels. The general trend was as the confidence was increased, the EE reduced and the RDT&E increased. Thus, for increasing confidence, or reduced risk, the likelihood of achieving the economic targets was very small, unless the threshold value could be negotiated.

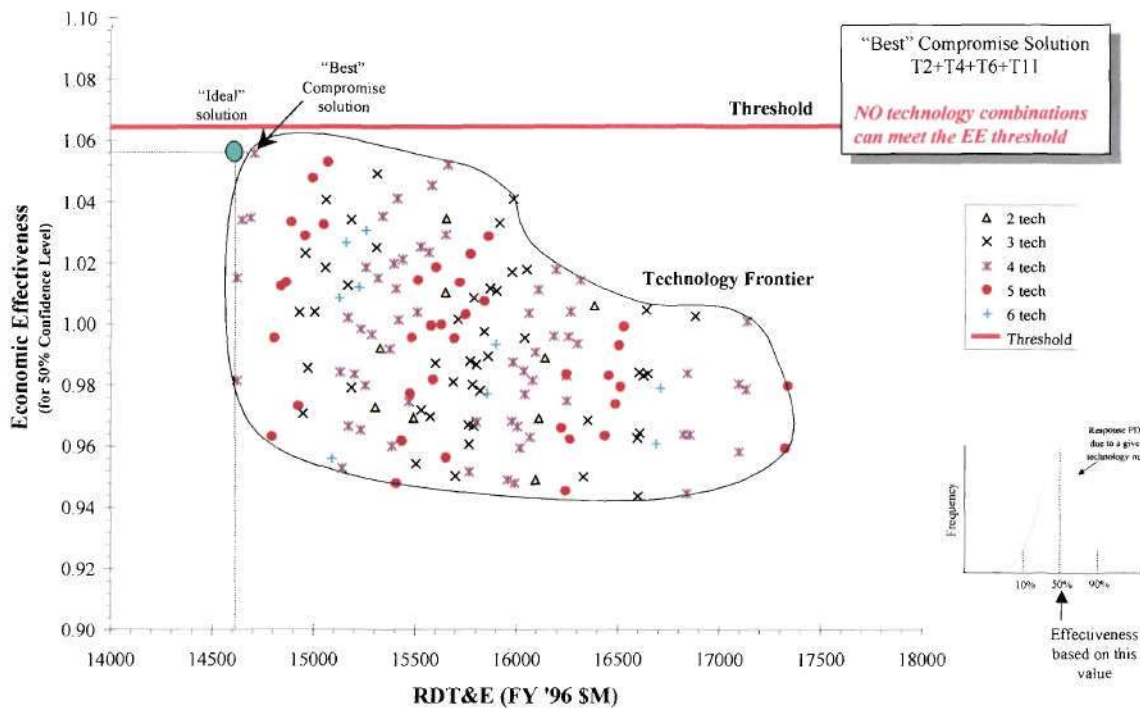


Figure 66: Economic Effectiveness with Uncertainty

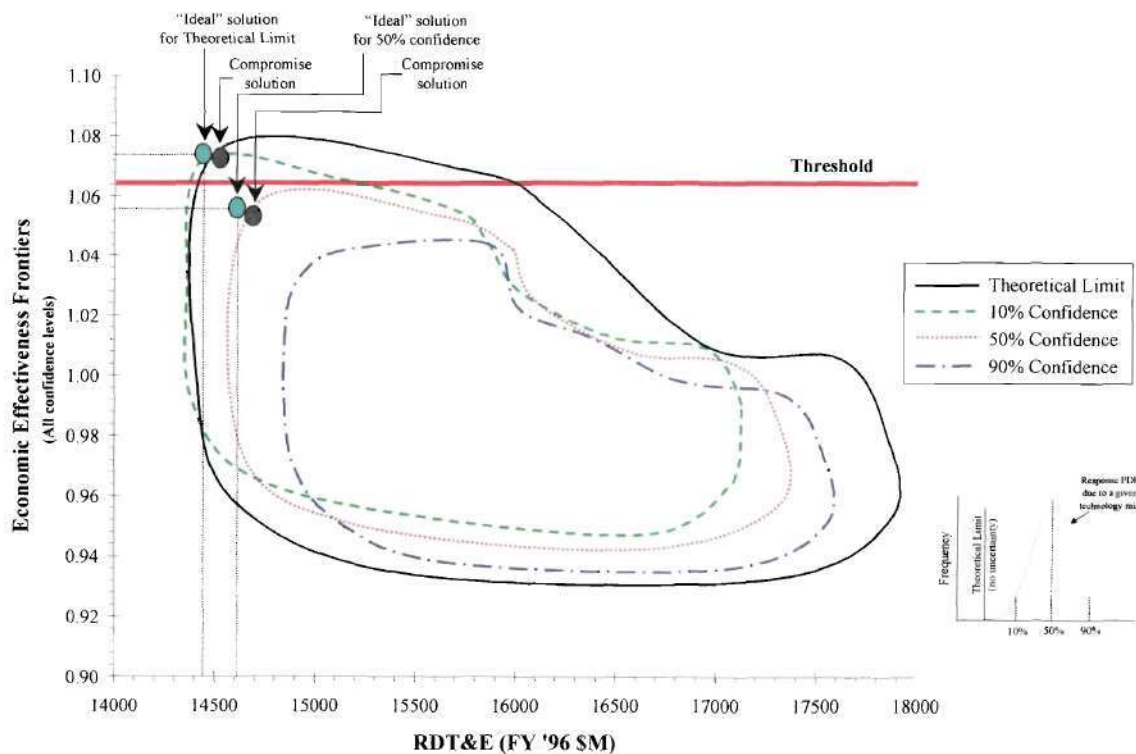


Figure 67: Comparison of Economic Effectiveness at Different Confidence Levels

System Effectiveness Frontier

For the System Effectiveness parameter, only the 50% confidence level is shown for brevity in Figure 68. The $SE_{\text{threshold}}$ value of 1.0518 was an equal balance of the $PE_{\text{threshold}}$ and the $EE_{\text{threshold}}$ established previously. Approximately 30% of the compatible and feasible alternatives *could meet* the threshold value. This was an erroneous result. As was shown in the EE frontiers at 50% confidence, no technology alternative could meet the $EE_{\text{threshold}}$. Hence, for the System Effectiveness parameter, the increase in the PE term dominated the reduction in the EE term. For this particular application of the TIES method, the SE frontier was not an appropriate selection option and will not be considered further.

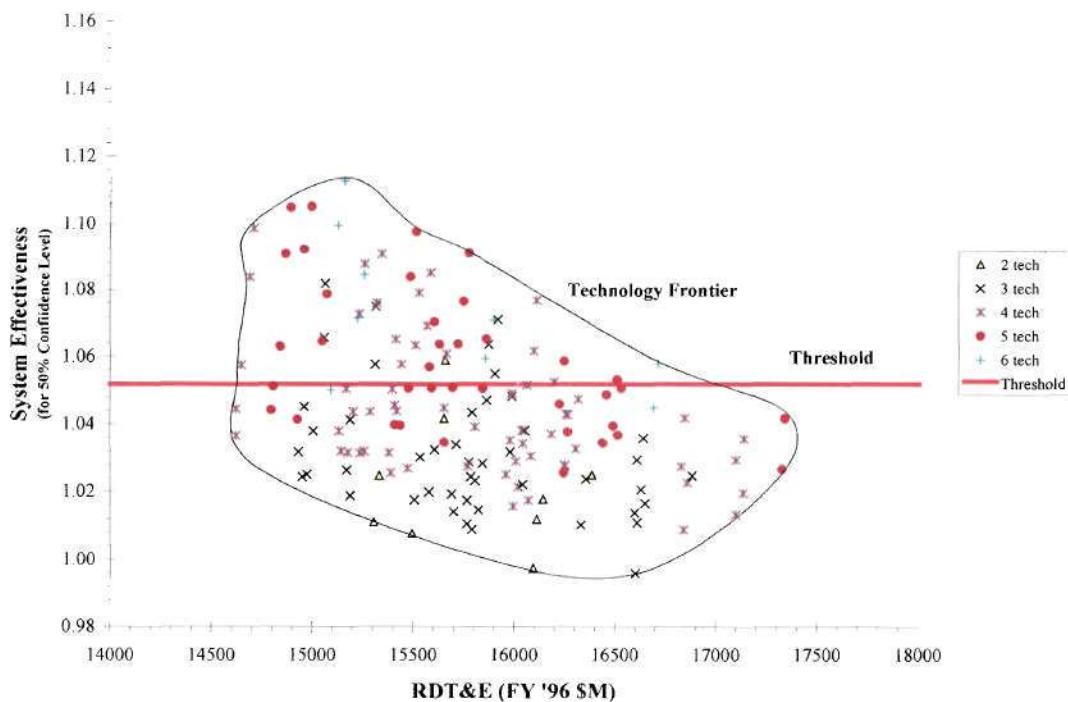


Figure 68: Combined System Effectiveness

As mentioned in Chapter I, the affordability of the system is of utmost importance. With the technology frontier approach, the affordability, or system cost effectiveness, could be quantified as ratio of the benefit supplied to the system in terms of PE to the cost to achieve that effectiveness in terms of EE. Hence, the affordability of the technology combinations considered could be compared based on the PE values versus the EE values and an affordability frontier could be established for the “theoretical” value and the different confidence levels. A comparison of the different affordability frontiers is depicted in Figure 69. Unlike the previous frontiers which desired a high effectiveness parameter with a minimum RDT&E costs, the affordability frontier desired a maximum of both the PE and EE values. Although the general shape of the frontiers changed in comparison to the PE and EE frontiers shown previously, the technology combinations that were closest to the “ideal” solution were T2+T3+T4+T6+T11 (as was the case in the PE frontiers) and T2+T4+T6+T7+T11 (as was the case in all weighting scenarios in TOPSIS). However, the EE threshold was based on an acquisition price of \$185M and could be adjusted to created more viable combinations. Also, the impact of increasing confidence level on the shifting of the frontiers observed for the PE and the EE was slightly modified in that the frontiers collapsed in area with increasing confidence level.

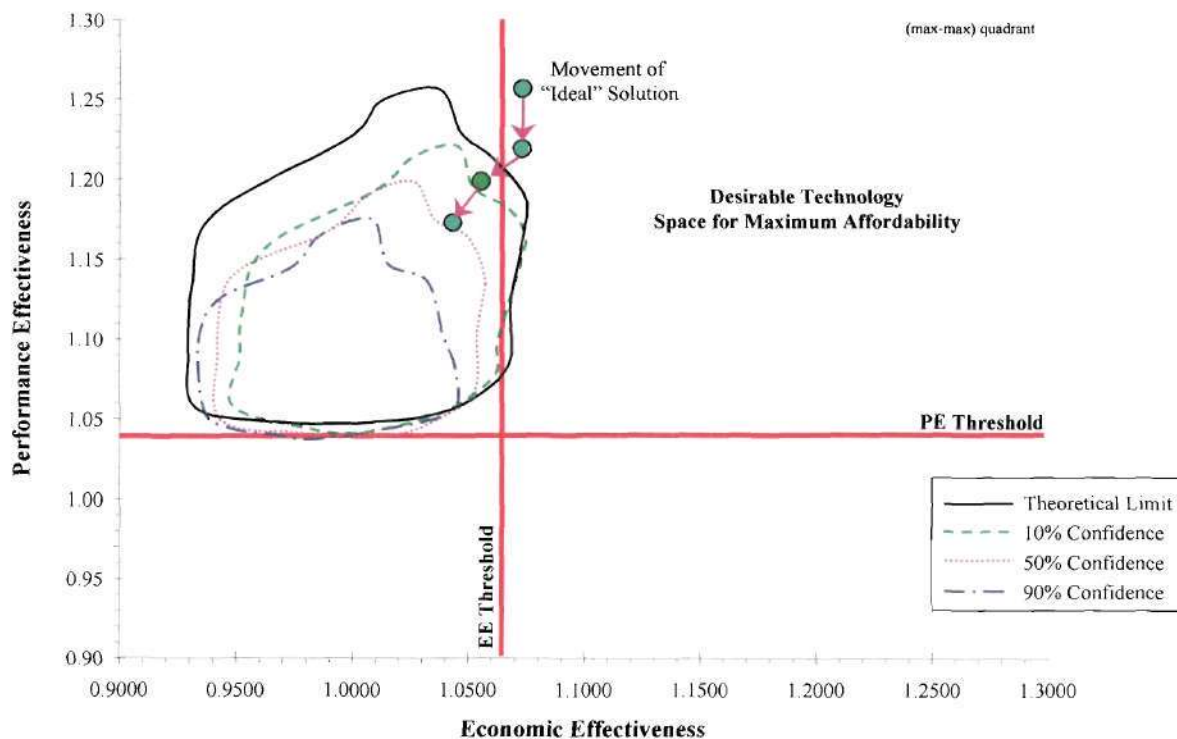


Figure 69: Comparison of Affordability Frontiers

Finally, a comparison of the ideal and compromised solutions was explored. For each DM for which a comparison was made, the “ideal” and the different confidence level solutions were identified and listed in Table XXIV. As was evident in each of the frontier plots, the “ideal” solution was reduced for increasing confidence levels for all effectiveness parameters. The most prominent technology mixes were T2+T3+T4+T6+T11 for the PE frontier and T2+T4+T6+T11 for the EE frontier, while the affordability frontiers resulted in a tossup between T2+T3+T4+T6+T11 and T2+T4+T6+T7+T11. This result would suggest that these particular mixes of technologies were superior. Yet, the EE alternative could not achieve the acceptable EE threshold value for confidence levels greater than 10% and may introduce too much risk if chosen as the only alternative.

Table XXIV: Summary of Best and Compromised Solutions

Confidence Level	PE Frontiers (RDT&E, PE)	EE Frontiers (RDT&E, EE)
<i>Theoretical Limit "Ideal" Solution</i>	(\$14,451M, 1.2567)	(\$14,451M, 1.0735)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$14,742M, 1.2287)	T2+T4+T6+T11 (\$14,529M, 1.0735)
<i>10% Confidence "Ideal" Solution</i>	(\$14,387M, 1.2196)	(\$14,387M, 1.0733)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$14,631M, 1.1969)	T2+T4+T6+T11 (\$14,467M, 1.0733)
<i>50% Confidence "Ideal" Solution</i>	(\$14,621M, 1.1986)	(\$14,621M, 1.0557)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$14,890M, 1.1764)	T2+T4+T6+T11 (\$14,706M, 1.0557)
<i>90% Confidence "Ideal" Solution</i>	(\$14,863M, 1.1727)	(\$14,863M, 1.0433)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$15,173M, 1.1514)	T2+T4+T6+T11 (\$14,979M, 1.0350)

Resource Allocation

Each of the dominant alternatives in the two previous selection techniques contained at least four technologies. However, the risk associated with undertaking the development of more than a few technologies concurrently is very high. It is unlikely that a company has the expendable R&D budget and resources to successfully develop more than one or two technologies in house and jeopardize the future of the company. As stated previously, all technologies were assumed to have a successful development program. This assumption implied that the appropriate amount of funds and resources might be used at any given time to develop the technology. This would not be true for a real program for which a development budget limit would exist. Hence, as a decision-maker,

guidance was desired as to which technology would be most influential for R&D resource allocation to overcome constraints or meet customer requirements.

Resource allocation quantification was performed through a comparison of the individual technologies to the conventional optimized configuration, along with evaluating the metric value deviations. The SLN and the \$/RPM are shown in Figure 70 and Figure 71, respectively. For the SLN, the target percent reduction needed to obtain a feasible concept was 7.28% from the optimized baseline generated at the beginning of Step 6, as indicated by the vertical line. Both engine concepts (T5 and T11) provided the needed reduction with a confidence level of approximately 60%. Hence, either one would be prime targets for increased R&D resources.

One must also consider the impact of the technology on the system in terms of affordability and other performance metrics. As shown in Figure 71, T5 and T11 increased the \$/RPM and could potentially hinder the success of the program. As for other performance metrics, T5 increased the V_{app} for all confidence levels to a point where the constraint value of 155 kts was violated by as much as 4.5 kts at the 100% confidence level. T5 negatively impacted all metrics except for FON and SLN. To the decision-maker, the further development of the environmental engines (T5) should be in question, unless another technology was infused to counter the negative impact. One example would be HLFC (T4). HLFC countered the negative impact of T5 by reducing all metrics. If a company could invest the resources needed for both technologies, the metrics targets could be achieved. A similar result was obtained for T11, and the same *trade-off rationale could be applied*. As shown with TOPSIS and the frontiers, T2, T4, and T6 were dominant technologies. In the resource allocation investigation, a similar

result was obtained, with exception of increased acquisition price for T2 and T4 at all confidence levels. Although none of the technologies could provide the needed SLN reductions, all three provide sufficient benefits to the other metrics to improve upon the imposed metrics.

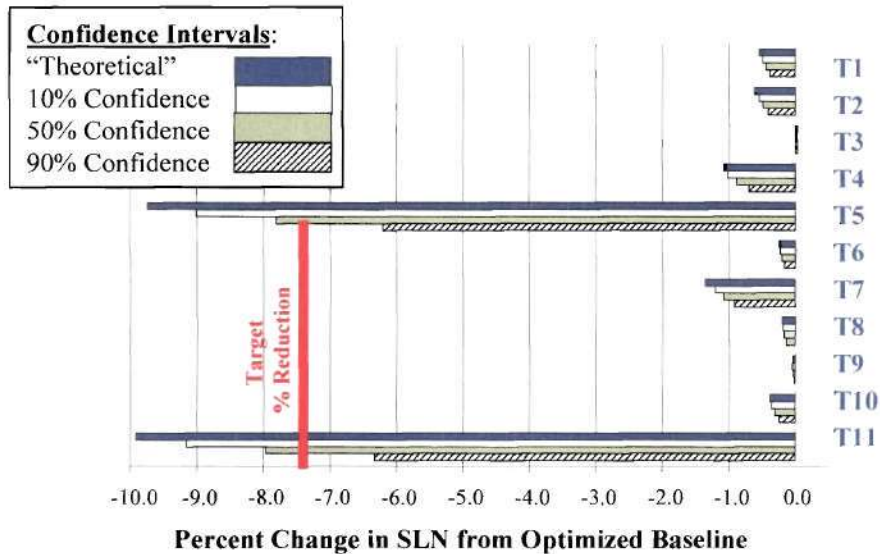


Figure 70: Probabilistic Impact of Technologies on SLN

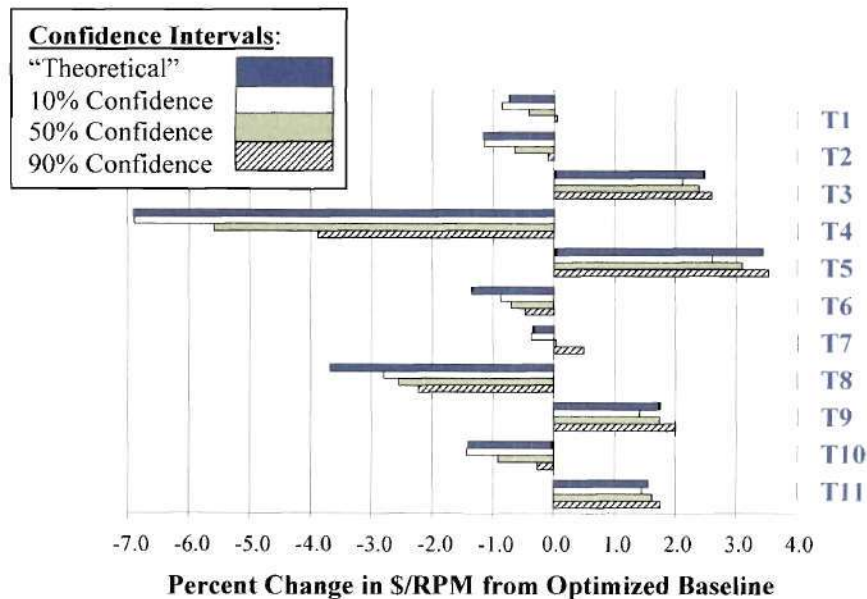


Figure 71: Probabilistic Impact of Technologies on \$/RPM

“Best” Family of Alternatives: Re-Investigate the Design Space

The design of any complex system does not result in a single configuration that maximizes customer satisfaction and was due to the subjectivity of the selection problem and the techniques by which the alternatives were quantified. Thus, three options were posed to provide a cross-section of selection techniques, while accounting for subjectivity, to identify a family of alternatives that could be investigated in further detail. The three selection techniques resulted in the following “best” family of alternatives:

TOPSIS:

Any combination of T2+T4+T6, while the top performers for all weighting scenarios were T2+T3+T4+T6+T11, T2+T4+T6+T7+T11, and T2+T3+T4+T6+T7+T11

Technology Frontiers:

Performance Effectiveness: T2+T3+T4+T6+T11 for all levels considered

Economic Effectiveness: T2+T4+T6+T11 for all confidence levels while T2+T6+T8+T10+T11 could meet the $EE_{\text{threshold}}$ for low confidence levels

Affordability: tossup between T2+T3+T4+T6+T11 and T2+T4+T6+T7+T11 for all confidence levels

Resource Allocation:

Results also showed that T2+T4+T6 were the most significant technologies that improved all system metrics, but SLN could not be met without the addition of an engine concept, such as T5 or T11

From the three selection techniques, 6 technology combinations were considered for further investigation as listed in Table XXV. Unfortunately, all of the alternatives contained at least 4 technologies. As a consequence, to obtain a feasible and viable HSCT concept, significant technology advances were a necessity as was eluded to when the HSCT concept was chosen as the test-bed for the TIES method. However, one option still remains to the decision-maker. More aggressive technologies (than the ones considered herein) could be identified to provide more substantial improvements and allow for a lower number of technologies to be infused. This option was not pursued herein.

Table XXV: “Best” Family of Alternatives

Alternative	Technology Combinations
1	T2+T4+T5+T6
2	T2+T4+T6+T11
3	T2+T4+T6+T7+T11
4	T2+T3+T4+T6+T11
5	T2+T6+T8+T10+T11
6	T2+T3+T4+T6+T7+T11

For each technology alternative listed in Table XXV, the level of technology was fixed at the “theoretical” value and the design space was re-investigated. The level of technology was fixed due to the correlation between design variables and technologies, i.e., “k” factors. Correlation of variables implies that the independent variables are directly correlated and cannot be selected independently of each other. *What exactly does this statement imply?* The answer to this question is best explained through example. Hypothetically, if the design variables and technologies were not correlated, the influence

of a technology, in the form of a Δk , would be *constant* throughout the design space, as shown on the left in Figure 72. Yet, the effect of correlation will change the influence of a technology throughout the design space in a manner not easily predicted or mathematically simple such that the Δk is *not constant* as shown on the right. A solution to this problem is to hold either the configuration or the technologies constant and then iterate to find an optimal solution. This was the approach taken herein, but is discussed in the recommendations to follow.

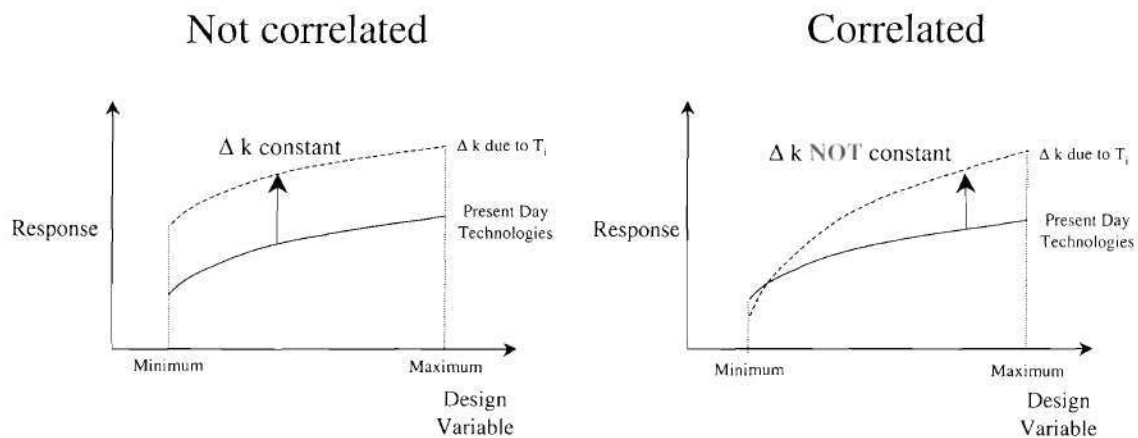


Figure 72: Statistical Relation Between Design Variables and Technologies

Given the 6 top performers, Steps 4 and 5 of the TIES method were repeated with the design space defined in Table VIII. The 6 technology alternatives were defined with the “k” vectors set at the “theoretical” values and the system feasibility was quantified. Comparing the amount of feasible space for each alternative revealed that Alternatives 2 and 3 had the highest feasibility and viability percentages than any others considered, as listed in Table XXVI. Alternative 2 and 3 had the largest viability percentage for \$/RPM.

Alternative 2 was deemed the “best” mix of technologies since only 4 technologies were needed while obtaining the highest feasible space with respect to \$/RPM. One should note that the impact of each technology applied was at the “theoretical” level. Thus, the feasibility values shown for each alternative *would* reduce once the technological uncertainty was reintroduced. One might conclude that the technologies chosen for infusion were not sufficient to create a feasible and viable HSCT concept, and more aggressive technologies *should be infused*.

Recall from the selection techniques, T2, T4, and T6 were prominent technologies, again, these three technologies appeared. The only difference between Alternative 2 and 3 was the addition of T7 on Alternative 3. The shift in the design space for these two alternatives is shown in Figure 73 in the form of metric PDFs. Both alternatives substantially improved the SLN, while the \$/RPM was moderate. Yet, the design space distributions were much closer to the \$0.10 target than the conventional configuration. The conventional configuration design space required at least an 8% improvement in SLN and a 20% improvement in \$/RPM to achieve a 25% feasible design space. Alternative 2 achieved more than an 8% reduction in SLN, but only a 7.1% reduction in \$/RPM, as shown in Figure 74.

Table XXVI: System Feasibility Comparison of Technology Alternatives

Metric (Target)	Conventional	Alternative 1 (T2+T4+T5+T6)	Alternative 2 (T2+T4+T6+T11)	Alternative 3 (T2+T4+T6+T7+T11)	Alternative 4 (T2+T3+T4+T6+T11)	Alternative 5 (T2+T6+T8+T10+T11)	Alternative 6 (T2+T3+T4+T6+T7+T11)
TOGW (750,000 lbs)	0%	18.7%	30.8%	54.5%	31.0%	2.9%	55.0%
TOFL (11,000 ft)	18.7%	84.5%	89.3%	94.7%	90.2%	49.4%	95.1%
LdgFL (11,000 ft)	87.1%	100%	100%	100%	100%	100%	100%
Vapp (155 kts)	3.3%	96.0%	97.0%	98.5%	100%	69.0%	100%
FON (106 EPNLdB)	3.1%	100%	100%	100%	100%	100%	100%
SLN (103 EPNLdB)	0%	100%	100%	100%	100%	100%	100%
\$/RPM (\$0.10)	0%	2.2%	2.7%	2.5%	1.7%	0.6%	0.5%

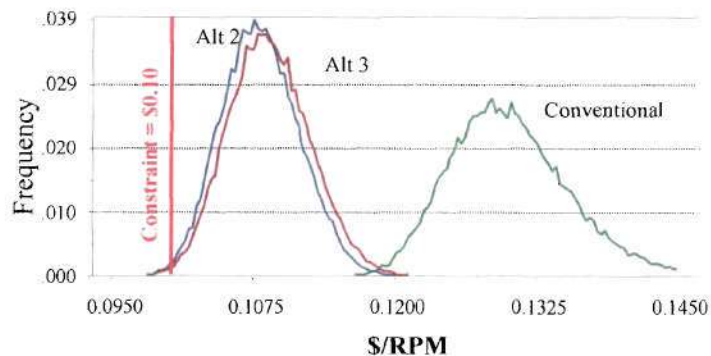
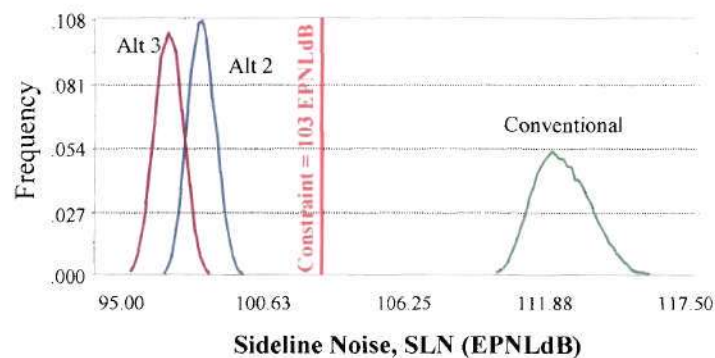


Figure 73: Design Space Comparison of Technology Alternatives

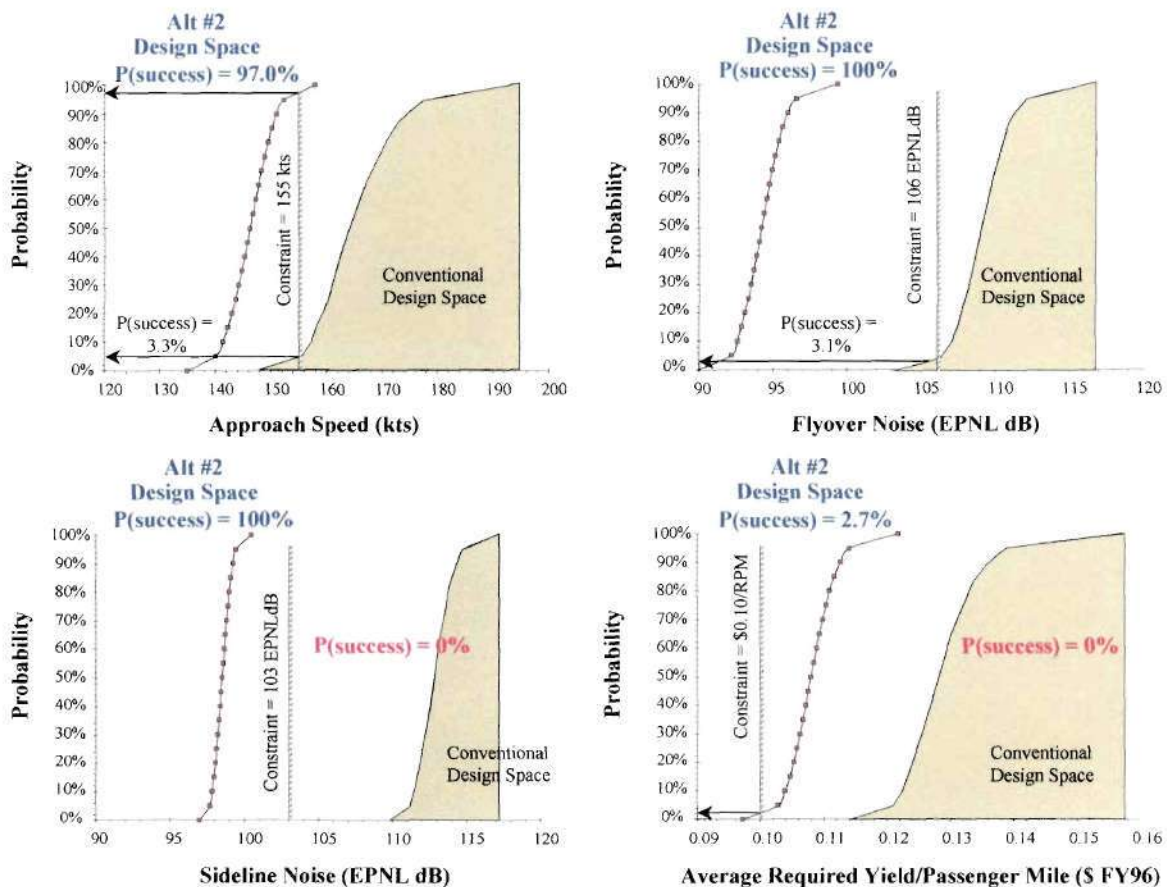


Figure 74: Shift in Design Space for Alternative 2

One final aspect of TIES was closure on the best configuration for a given level of technology, in this instance, Alternative 2 consisting of T2+T4+T6+T11. The desirability function of JMP was utilized to optimize the design variables for Alternative 2. A design space comparison to the original baseline is listed in Table XXVII. Alternative 2 required a smaller wing area and fan pressure ratio and a higher turbine inlet temperature and overall pressure ratio. Only modest deviations resulted from the wing planform geometry, but the thickness to chord ratios increased at the root and reduced at the tip for Alternative 2. The largest deviation in wing planform was the location of the trailing edge king location where Alternative 2 had a straight taper on the trailing edge and the original

baseline had a more distinctive double-delta shape. A comparison of the original baseline (solid model) and the optimized geometry (wireframe model) for Alternative 2 is depicted in Figure 75. The performance and economic metrics differences are listed in Table XXXII. The significant reductions in the metrics suggest that Alternative 2 is more efficient aircraft. Additionally, the required thrust for Alternative 2 was significantly lowered from 68,000 lb per engine to just over 45,000 lbs.

Table XXVII: Alternative 2 Optimal Geometry

Variable	Original Baseline	Alternative 2	Units	Description
SW	9000	8668	ft ²	Wing Area
TWR	0.29	0.29	~	Thrust-to-weight ratio
TIT	3000	3400	°R	Turbine Inlet Temperature
FPR	4.5	3.5	~	Fan Pressure Ratio
OPR	18	21	~	Overall Pressure Ratio
CLdes	0.1	0.1093	~	Design Lift Coefficient
X2	1.609	1.6306	~	LE kink x-location
X3	2.36	2.36	~	LE tip x-location
X4	2.58	2.58	~	TE tip x-location
X5	2.19	2.37	~	TE kink x-location
X6	2.18	2.18	~	TE root x-location
Y2	0.51	0.5114	~	LE kink y-location
t/c_root	4	5	%	Wing root thickness-to-chord ratio
t/c_tip	3	2	%	Wing tip thickness-to-chord ratio
SHref	550	400	ft ²	Horizontal Tail Area
SVref	450	350	ft ²	Vertical Tail Area

Baseline configuration (solid)
Alternative 2 (wireframe)

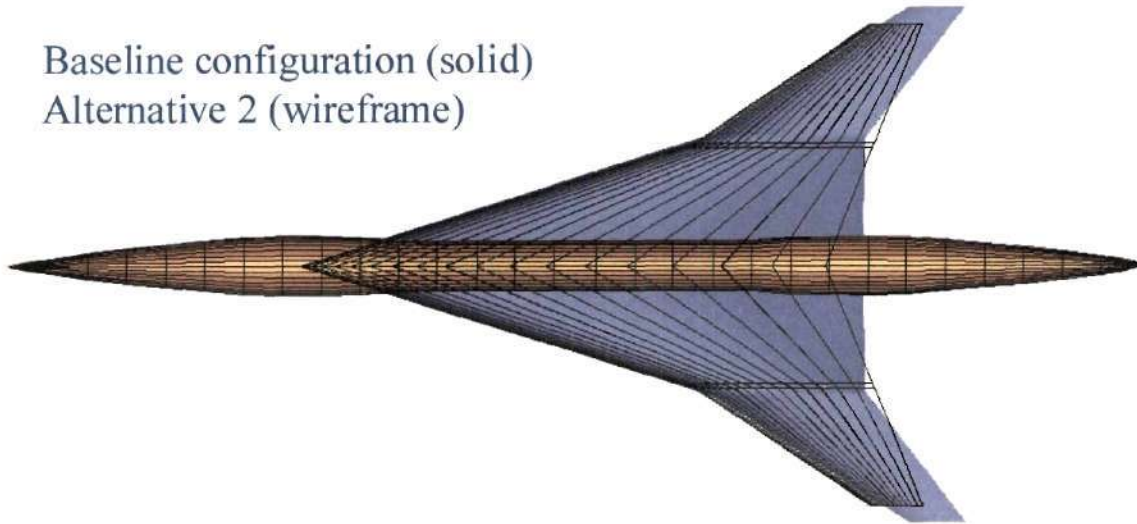


Figure 75: Comparison of Baseline Geometry to Alternative 2

Table XXVIII: Metric Comparisons of Alternative 2 and Baseline

Parameter	Baseline Configuration	Alternative 2
<u>Performance</u>		
Vapp	154.1 kts	129.26 kts
FON	112.3 EPNLdB	89.7 EPNLdB
LdgFL	9,063.2 ft	6,767.5 ft
SLN	111.6 EPNLdB	96.6 EPNLdB
TOFL	12,407 ft	8,023 ft
TOGW	937,108 lbs	627,198 lbs
<u>Economics</u>		
Acq\$	218.58 FY96 \$M	182.97 FY96 \$M
RDT&E	16,124.9 FY96 \$M	14,373.9 FY96 \$M
\$/RPM	0.1236 FY96 \$	0.0925 FY96 \$
TAROC	5.948 FY96 ¢	4.215 FY96 ¢
DOC+I	5.058 FY96 ¢	3.520 FY96 ¢

Example 2: Modified Assumptions for Technology Readiness Levels

One aspect of the hypothesis statement for this dissertation was a rapid and efficient probabilistic design environment to provide the decision-maker with sufficient knowledge whereby more informed decision could be made in the early phases of design. Example 2 of this Chapter exemplified this aspect. In particular, the environment that was created as a result of Example 1 was slightly modified and the “best” solutions were re-examined. Specifically, the 11 technologies in Example 1 were defined at Technology Readiness Levels (TRLs) of 3 or 4. In this example, 6 of the 11 technology TRLs were modified as listed in Table XXIX and the selection step re-executed. Another aim of this example was to determine the sensitivity of varying the TRLs on the “best” alternatives previously identified in terms of absolute rankings and overall performance.

Table XXIX: Modified Technology TRL

(Identifier) Technology	Example 1 TRL	Example 2 TRL
(T1) Composite Wing	3	4
(T2) Composite Fuselage	3	2
(T3) Circulation Control	4	4
(T4) Hybrid Laminar Flow Control	3	6
(T5) Environmental Engines	3	5
(T6) Advanced Flight Deck Systems	4	6
(T7) Advanced Propulsion Materials	3	3
(T8) Integrally Stiffened Aluminum Wing Structure	4	4
(T9) Smart Wing Structures	3	2
(T10) Active Flow Control	3	3
(T11) Acoustic Control	3	3

The Technology Compatibility Matrix (TCM) and the Technology Impact Matrix (TIM) remained identical from Example 1. The only steps of the method that required re-execution were portions of Step 7 (Technology Evaluation) and the entire Step 8 (Technology Selection). The robustness of the TIES method was discussed as the RSEs for the system metrics as a function of technology “k” factors were defined in Step 7 of Example 1. Once the equations were generated, only the assumptions associated with the technology vectors, i.e., the technology vector elements or “k” factors, needed alteration. Since each metric was defined as a function of the technology space limits in the TIM (Figure 45), the metric RSEs were still valid and did not need to be regenerated. The TRL Weibull distributions were modified based on the new TRLs in Table XXIX as defined by Equation 37 and the Monte Carlo Simulation was performed. Only the compatible technologies were assessed for this example. Once the probabilistic metric information was extracted for each compatible technology combination, the four Decision Matrices (DMs) were created (“theoretical” and 10%, 50%, and 90% confidence levels). The three selection techniques were again applied and the “best” alternatives selected and compared to the previous example. The same structure for the selection step in Example 1 was followed.

Step 8: Technology Selection (Example 2)

MADM: TOPSIS

TOPSIS was applied to the new DMs with the same weighting scenarios defined in Table XX. As was the case in Example 1, 7 technologies appeared in the top 15 for each weighting scenario. In fact, the technology combinations were identical as was listed in

Table XXI. The influence of the new TRLs was obvious upon inspection of each technology alternatives' rank and closeness value. Again, weighting Scenarios #1 and #9 were compared to the previous results as listed in Table XXX and Table XXXI, respectively. Scenario #1 was weighted heavily towards the performance metrics of FON and SLN. Concept 505 (T2+T3+T4+T5+T6+T7), which ranked high for performance weightings, improved in closeness value and rank relative to Example 1 due to the increase in TRLs of T4, T5, and T6.

However, Concept 1481, which contained T2+T3+T4+T7+T11, reduced in rank and closeness value due to the reduction of readiness level of T2. Technologies T4, T5, and T6 readiness levels were increased in this example, and the impact was observed in concept 377, which contained T2+T4+T5+T6+T7. The absolute rank of concept 377 substantially increased at high confidence levels since the variability of the metrics reduced with increasing TRL. The highest ranking concept in Example 1 for Scenario #1 was concept 1497, which contained T2+T3+T4+T6+T7+T11. This again was the case and the concept closeness value increased due to T4 and T6 increasing in TRL. These trends were consistent for Scenario #9, except that concept 1369 (T2+T4+T6+T7+T11) surfaced as the top alternative for all confidence levels, as listed in Table XXXI. For a second time, concepts 505 and 1481 could not meet the imposed \$/RPM constraint as in Example 1 and T2, T4, and T6 were the dominant technologies infused, although the composite fuselage (T2) TRL was reduced.

Table XXX: TOPSIS Comparison for Top Mixes for Weighting Scenario #1

Concept Number	Example 1			Example 2		
	<u>10%</u> Confidence Closeness (Rank)	<u>50%</u> Confidence Closeness (Rank)	<u>90%</u> Confidence Closeness (Rank)	<u>10%</u> Confidence Closeness (Rank)	<u>50%</u> Confidence Closeness (Rank)	<u>90%</u> Confidence Closeness (Rank)
377	0.7737 (10)	0.7529 (13)	0.7226 (13)	0.7764 (10)	0.7611 (9)	0.7417 (8)
505	0.7997 (6)	0.7762 (6)	0.7448 (8)	0.8023 (6)	0.7842 (6)	0.7608 (5)
1361	0.7845 (9)	0.7686 (7)	0.7411 (9)	0.7874 (8)	0.7694 (8)	0.7398 (9)
1369	0.8415 (4)	0.7975 (3)	0.7720 (3)	0.8170 (3)	0.8016 (3)	0.7791 (3)
1481	0.8145 (3)	0.7927 (4)	0.7632 (5)	0.8155 (4)	0.7926 (4)	0.7607 (6)
1489	0.8385 (2)	0.8170 (2)	0.7865 (2)	0.8408 (2)	0.8048 (2)	0.7817 (2)
1497	0.8449 (1)	0.8231 (1)	0.7942 (1)	0.8477 (1)	0.8274 (1)	0.8019 (1)

Table XXXI: TOPSIS Comparisons for Top Mixes for Weighting Scenario #9

Concept Number	Example 1			Example 2		
	<u>10%</u> Confidence Closeness (Rank)	<u>50%</u> Confidence Closeness (Rank)	<u>90%</u> Confidence Closeness (Rank)	<u>10%</u> Confidence Closeness (Rank)	<u>50%</u> Confidence Closeness (Rank)	<u>90%</u> Confidence Closeness (Rank)
377	0.7619 (5)	0.7379 (6)	0.7050 (8)	0.7633 (5)	0.7454 (5)	0.7236 (5)
505	0.7473 (10)	0.7206 (14)	0.6848 (15)	0.7496 (10)	0.7293 (10)	0.7038 (11)
1361	0.8066 (2)	0.7886 (1)	0.7610 (1)	0.8106 (2)	0.7911 (2)	0.7632 (2)
1369	0.8078 (1)	0.7862 (2)	0.7568 (2)	0.8113 (1)	0.7925 (1)	0.7677 (1)
1481	0.7486 (9)	0.7232 (12)	0.6898 (13)	0.7510 (9)	0.7255 (12)	0.6925 (13)
1489	0.8047 (3)	0.7799 (3)	0.7463 (3)	0.8084 (3)	0.7823 (3)	0.7513 (3)
1497	0.7944 (4)	0.7683 (4)	0.7344 (4)	0.7979 (4)	0.7751 (4)	0.7481 (4)

Technology Frontiers

The effectiveness parameters and threshold values defined in Example 1 were also utilized for Example 2. In Example 1, only 134 of the original 272 compatible combinations were feasible at the 90% confidence level. However, once the TRLs were modified for 6 of the 11 technologies, 16 more alternatives were feasible at the 90% confidence level, raising the total to 150. For brevity, only the frontiers are discussed.

A comparison of the PE frontiers for the old TRLs (Example 1) and the new TRLs (Example 2) is depicted in Figure 76. The primary impact of modifying the TRLs was observed to be an increase in the PE values at high confidence levels as seen by the shift in the “ideal” solution and the “compromise” solution. The left edge of each frontier was pushed to higher PE value and lower RDT&E for each confidence level which was consistent for the definition of the impact of technological uncertainty on performance metrics. That is, as the maturity of a technology increases, the impact should approach the “theoretical” impact level. This was in fact the trend observed. Similarly for the EE frontiers, shown in Figure 77, the “ideal” and “compromise” solutions moved closer to the “theoretical” solutions as seen by shift in the frontiers in the top left hand corner. The largest gains in EE were for higher confidence levels as the amount of technology space captured for the 90% confidence level increased from Example 1.

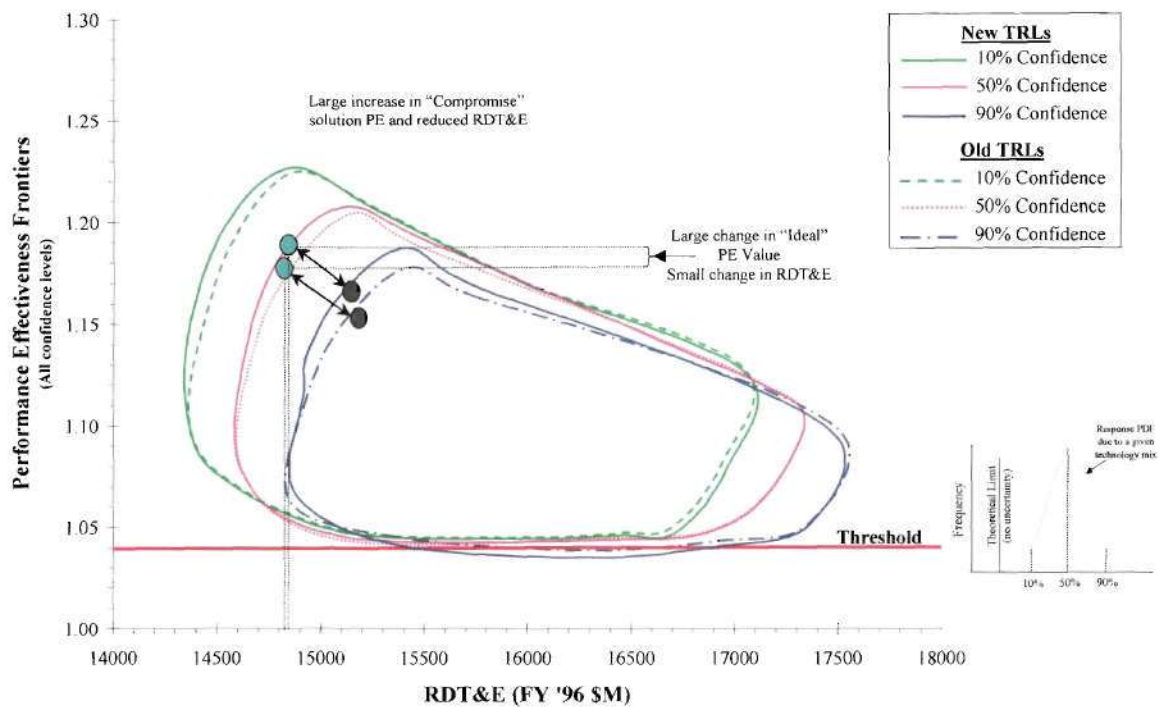


Figure 76: Comparison of Performance Effectiveness

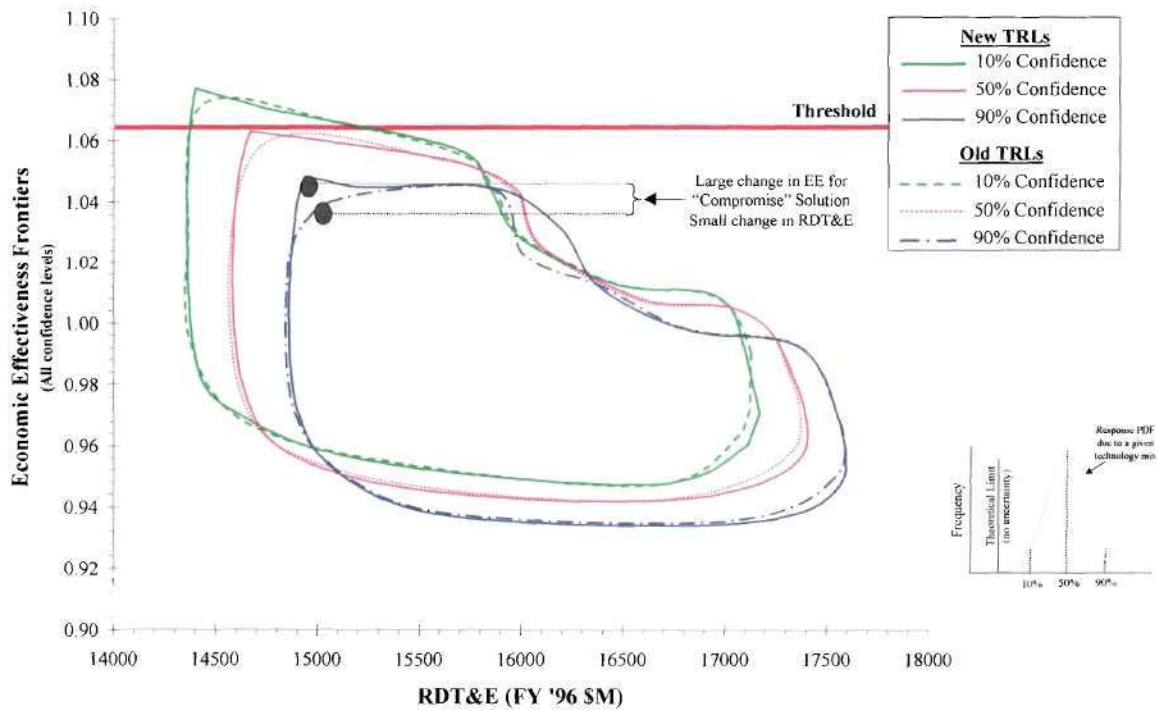


Figure 77: Comparison of Economic Effectiveness

The best means of determining the impact of changing the TRLs was through a comparison of the “ideal” and “compromised” solutions for the two examples as listed in Table XXXII. Although the technology combinations remained identical in both cases, the absolute values in PE, EE, and RDT&E varied. The “best” compromise solution PE and EE values improved since both alternatives contained T2, T4, and T6.

Table XXXII: Comparison of Best and Compromised Solutions for Example 1 and 2

Confidence Level	Example 1		Example 2	
	PE Frontiers (RDT&E, PE)	EE Frontiers (RDT&E, EE)	PE Frontiers (RDT&E, EE)	EE Frontiers (RDT&E, EE)
10% Confidence “Ideal” Solution	(\$14,387M, 1.2196)	(\$14,387M, 1.0733)	(\$14,411M, 1.2237)	(\$14,411M, 1.0755)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$14,631M, 1.1969)	T2+T4+T6+T11 (\$14,467M, 1.0733)	T2+T3+T4+T6+T11 (\$14,615M, 1.2007)	T2+T4+T6+T11 (\$14,431M, 1.0755)
50% Confidence “Ideal” Solution	(\$14,621M, 1.1986)	(\$14,621M, 1.0557)	(\$14,644M, 1.2063)	(\$14,644M, 1.0619)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$14,890M, 1.1764)	T2+T4+T6+T11 (\$14,706M, 1.0557)	T2+T3+T4+T6+T11 (\$14,855M, 1.1834)	T2+T4+T6+T11 (\$14,676M, 1.0619)
90% Confidence “Ideal” Solution	(\$14,863M, 1.1727)	(\$14,863M, 1.0433)	(\$14,890M, 1.1855)	(\$14,890M, 1.0465)
Compromised Technology Solution	T2+T3+T4+T6+T11 (\$15,173M, 1.1514)	T2+T4+T6+T11 (\$14,979M, 1.0350)	T2+T3+T4+T6+T11 (\$15,120M, 1.1627)	T2+T4+T6+T11 (\$14,947M, 1.0465)

The increase in PE and EE values was rather intuitive. However, the increase in the RDT&E was explained based on the original definition of the economic “k” factors for each technology. An assumption was made when the technological uncertainty was modeled as a Weibull distribution. Recall from Figure 48 that the location (or anchor point) of the Weibull distribution corresponded to the “theoretical” value listed in the Technology Impact Matrix (TIM) and resulted in the minimum value that the “k” factor

would ever achieve. However, when a technology negatively impacted a given disciplinary metric, such as increasing the RDT&E, the location of the Weibull distribution was assumed to be the “theoretical” value and became the *maximum* value that the “k” factor would have. From either perspective, no change from the baseline (or $k_i=0$) was a boundary as was described in the TRL Distribution Shape section. This point is best understood through visualization of a “k” factor variation with TRL, as depicted in Figure 78. As the TRL increased for an adverse “k” factor, the distribution shifts towards the “theoretical” value. In reality, this trend may not happen but for consistency of the variation of a “k” factor with TRL, this assumption was made. Hence, as the confidence level increased for the Economic Effectiveness parameter, the RDT&E also increased due to this assumption.

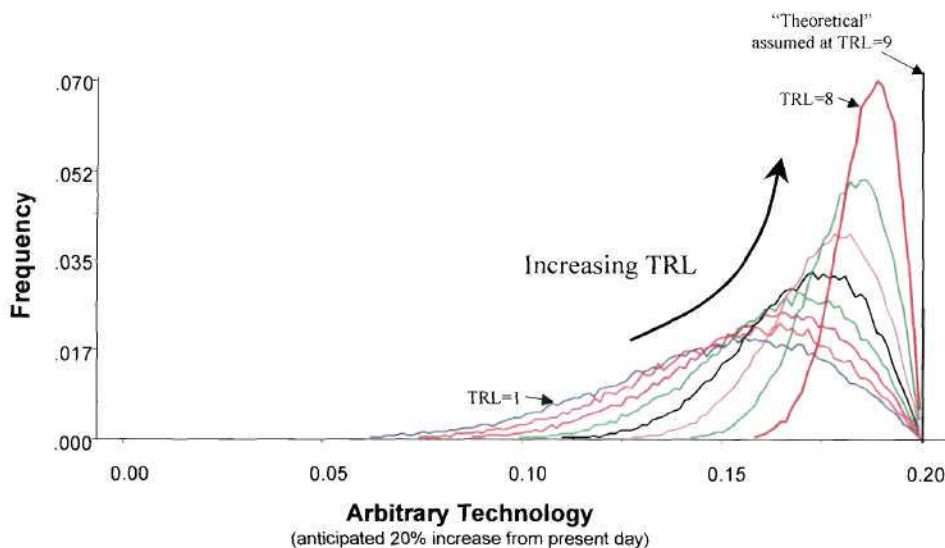


Figure 78: Variation of an Adverse “k” Factor with TRL

Resource Allocation

For the last selection technique, the relative change of each metric for a given technology was compared to the results obtained in Example 1. The SLN and \$/RPM are shown in Figure 79 and Figure 80, respectively. In Example 1, T5 and T11 could both meet the SLN constraint of 103 EPNLdB with approximately a 60% confidence. However, once the TRL for T5 was increased, the likelihood of achieving the constraint value increased to almost 95% confidence for T5, but remained at 60% for T11. From the two previous selection techniques, T11 remained superior to T5 and would be the choice for the noise suppression technology due to the minimal degradations to other metrics. Unfortunately in Figure 80, the degradation to the \$/RPM from the addition of the environmental engines (T5) also increased and suggested that T11 remained superior, although the risk of achieving the desired reduction was higher. The composite fuselage (T2), hybrid laminar flow control (T4), and the advanced flight deck (T6) remained as dominant technologies. Although the TRL for T2 was reduced, the impact on the feasibility and viability was not substantial enough to disregard the importance of infusing T2.

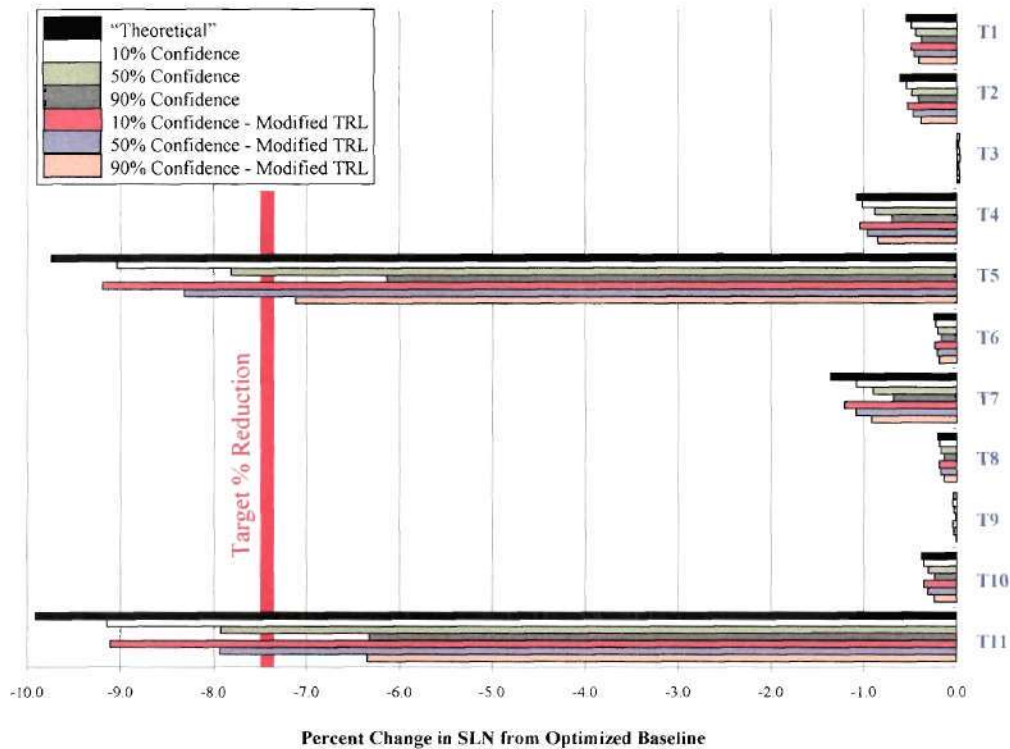


Figure 79: Comparison of the Impact of Varying TRLs on the SLN

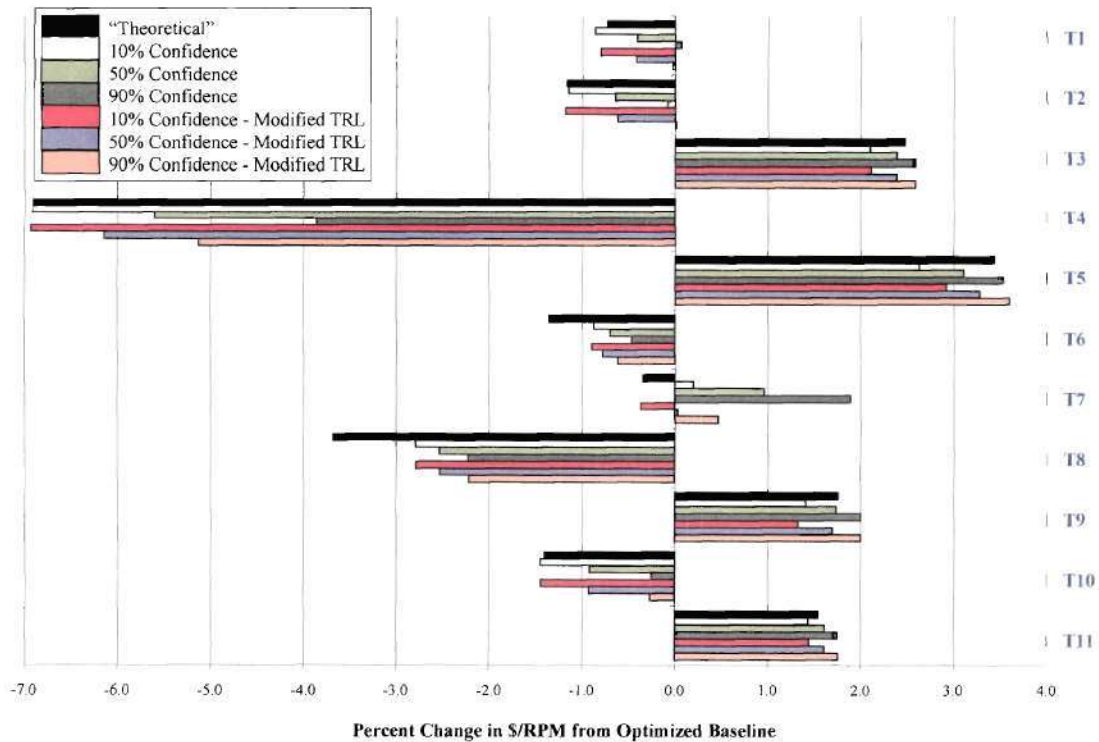


Figure 80: Comparison of the Impact of Varying TRLs on the S/RPM

Summary of Example 2

Two major conclusions were drawn from Example 2. First, the technology alternatives that were deemed as significant from Example 1 increased in superiority over the other alternatives. This could be a result of the fact that each alternative had a combination of T2, T4, and T6 which appeared to positively affect the system more than the other technologies considered, regardless of the selection technique. Further, as the TRL was increased, the resulting variability in the metrics reduced as the metric distributions shifted closer to the “theoretical” values and subsequently reduced the risk associated with developing those technology combinations.

CHAPTER V

CONCLUSIONS

The design of complex systems, such as commercial aircraft, has shifted its focus from the traditional design for performance to design for affordability and quality. This paradigm shift calls for solutions that are beyond historical databases and demands the consideration of all aspects of the system's life cycle. The shift implies that a new means of evaluating the "goodness" of an aircraft system must be established in lieu of the current system metrics, such as minimum gross weight or maximum performance. This dissertation has addressed these issues by creating a new design method which responds to the paradigm shift in aerospace systems design. This comprehensive and structured method, called the Technology Identification, Evaluation, and Selection (TIES) method, was developed with a knowledge of what was needed to respond to the paradigm shift and of the inefficiencies of current design methods. Drawing from the pertinent steps of existing design approaches, a generic, systems level method was established which began with defining the problem and concluded with selecting the best family of technology alternatives. The TIES method incorporates the elements of the new paradigm, in particular, life cycle considerations, breakthrough technologies, and new design methods.

The resulting design method includes a forecasting environment whereby the decision-maker has the ability to easily assess and trade-off the impact of various technologies without sophisticated and time-consuming mathematical formulations. Further, TIES provides a methodical approach where *technically feasible alternatives* can be identified with accuracy and speed to reduce design cycle time, and subsequently, life cycle costs, and was achieved through the use of various statistical and probabilistic methods, such as Response Surface Methodology and Monte Carlo Simulations. Furthermore, structured and systematic techniques were utilized from other fields to identify possible concepts and evaluation criteria by which comparisons can be made. This objective was achieved by employing the use of Morphological analysis, forecasting analogies and techniques, and Multi-Attribute Decision Making techniques. Through the execution of each step, a family of design alternatives for a given set of customer requirements can be identified and assessed subjectively or objectively. This methodology allows for more information or knowledge to be brought into the earlier phases of the design process and will have direct implications on the affordability of the system. The increased knowledge allows for optimum allocation of company resources and quantitative justification for program decisions. Finally, the TIES method provided novel results and quantitative justification to facilitate decision making in the early stages of design so as to produce affordable and quality products.

A proof of concept investigation was performed on a High Speed Civil Transport. This vehicle was used as a benchmark due to the technically challenging customer requirements and the need for revolutionary methods to forecast the impact of technological breakthroughs. The problem was defined in terms of a set of customer

requirements that included both performance and economic criteria. A space of concept alternatives was established via a Morphological analysis and further decomposed into a geometric and propulsive design space. Upon investigation of the design space, the sideline noise constraint was deemed as the performance “show-stopper”.

Subsequently, eleven technologies were infused into the HSCT concept. The Technology Readiness Level (TRL) of each technology was established through a literature review of applied research. From the search, the readiness levels were mapped to a probabilistic space such that technologies could be infused into the vehicle. Physically compatible technology combinations were evaluated and ranked based on the improvements to the customer requirements. The technology space investigation identified three technologies as significant for further investigation and include the use of composite fuselage structures, hybrid laminar flow control, and advanced flight deck systems. These technologies were established as prominent from various selection techniques such as Multi-Attribute Decision Making techniques, technology frontiers, and resource allocation. An additional investment of an advanced engine concept to reduce noise characteristics must be pursued to ensure compliance with FAR Stage III sideline noise requirements. A concept containing these technologies could meet all imposed customer requirements and created the largest feasible design space for which system trade-offs could occur.

As a result of the proof on concept application, specific intellectual contributions were made to advance the state-of-the-art in design methods in addition to the general method presented. The thrusts of the techniques developed were focused on the various milestones encountered during a technology development program. These milestones

were qualitative in nature and sufficient for program tracking, but were mapped to a quantitative scale for the purpose of decision making. The identification of the sources of technological uncertainty were described and applied to the determination of how that uncertainty could be modeled when a technology was infused to the system. Furthermore, the sensitivity of customer requirements to technological uncertainty was investigated providing valuable insight for mapping technological uncertainty to technology readiness.

Recommendations

The recommendations of future work and extensions of the presented method stem from the assumptions that were made as the method was developed. Although the TIES method is fairly robust and comprehensive, the method is not complete, nor fully matured. In the context of readiness levels, TIES is at a TRL of 5. Many suggestions are posed herein to extend and advance the current design method. The suggestions are not exhaustive, but are a starting point for future efforts.

First, the Response Surface Methodology (RSM) was extensively used throughout the TIES method. Two major assumptions were made such that the RSM was applicable. In particular, the input parameters for the Design of Experiments, i.e., design variables or technology “k” factors, were continuous; and the response could be approximated as a second order function. For the application considered herein, the assumption of a continuous space was sufficient. However, if any of the design variables or technologies considered required that the inputs to the Design of Experiments were discrete *and* continuous, a Response Surface Equation (RSE) could not be generated. An example of this situation would be a technology that affected the engine compressor such that the

number of stages could vary. At present, the Design of Experiments utilized required that each of the independent parameters be continuous. Thus, to model a response that is a function of continuous and discrete variables, an RSE would need to be generated for each discrete level across the continuous space. This is not a very efficient approach and should be addressed. Second, each of the responses considered was approximated as a second order function. However, circumstances may arise for different problems where a second order approximation would not be sufficient. Perhaps the response varied exponentially or logarithmically to one or more input parameters. Currently, one would handle this situation by modifying the range of the input parameter to rid of the non-quadratic nature or to break the input parameter into two ranges and create an RSE for each range. Again, neither approach is computationally efficient. Perhaps one solution would be to transform either the independent or the dependent variables such that the response would remain as a second order function or one could generate a higher-order approximation metamodel.

Next, any customer requirement is ultimately a function of the design variables, the technologies infused, and also, the design requirements, such as range or payload, each of which is not independent. Ideally, one would desire the capability to vary each of these concurrently to reduce the cycle time and reduce the number of iterations. However, the dependency between the design variables, technologies, and design requirements is not unique across the spectrum of vehicles that could be considered as was discussed in Chapter IV. Thus, a mathematical formulation is needed to establish the form of the correlation between these parameters. The approach taken herein was to fix either the technologies or the design space and iterate until a solution was determined. This

recommendation would require a rigorous mathematical development of the correlation between the design variables, technologies, and design requirements.

Moreover, the definition of the shape of the technological uncertainty as a function of TRL was based on the method of analogy. The assumption that the uncertainty would diminish as the technology was developed was made since insufficient data existed to establish any growth trend and apply rigorous forecasting techniques. Thus, the form of the technological uncertainty was based on what should happen in a successful development program. A better formulation would be made if actual technology data were available to establish the development trends. Unfortunately, compiling and collecting data from entities that have not tracked nor sufficiently monitored the progress of a technology is arduous. One possible solution to this dilemma is through a technique called Technology Opportunities Analysis pioneered by Porter [129]. Porter combines monitoring of a technology with a bibliometric analysis to create a “text mining” environment whereby intelligence on emerging technologies may be gathered. The results of this approach can be statistically analyzed to provide growth curves and trends for the technologies of interest. This is one potential source for data whereby a more justified form of the technological uncertainty as a function of TRL could be established.

Additionally, a natural extension of the TIES method would be to determine which technologies would have the highest payoff across a fleet of aircraft or multiple products. In lieu of just one vehicle concept being the focal point for technology infusion, a diverse group of vehicle concepts should be considered to cross-fertilize the technologies and maximize the return on investment. In doing so, the investment cost could be distributed amongst numerous vehicles and the risk of investment minimized for each. In addition,

some of the technologies that may have been disregarded for a particular investigation may in fact have a significant impact on a different class of vehicles. Thus, if a company was attempting to identify how to distribute a limited research and development budget, the applicability of a technology across many potential future concepts should be considered in the context of long-term strategic planning.

Furthermore, during the execution of Step 8 (Technology Selection), the selection of the best family of design alternatives was based on a particular confidence level, or a point estimate. For each confidence level, the highest ranking or best alternatives were identified and compared for the different selection techniques. This was a simplistic approach to determine the influence of technological uncertainty on the system metrics and identify the best mix of technologies. However, more rigorous approaches to evaluating uncertainty could be implemented. A strong example of these approaches are the robust design techniques pioneered by Taguchi. Although Taguchi's techniques are generally applied to tolerances associated with manufacturing processes, the analogy could be extended to technological uncertainty. The primary goal of Taguchi's approach is to minimize the deviation in a metric from the ideal or target value. The ideal value would be analogous to the "theoretical" impact of a technology on the system metrics. Thus, minimizing the deviation can minimize the loss to the system due to the variation from the ideal value [130]. This is analogous to reducing the variability of a system metric when the readiness level of a technology was increased. Thus, the potential exists to incorporate some of Taguchi's notions of robustness. Further, other robust design techniques, such as Motorola's Six Sigma program could be utilized. The program is based on the idea that a product or system has a capability of meeting a specified

tolerance, or in this case, level of variability in the metrics. Given this, a capability index, C_p , could be defined as

$$C_p = \frac{USL - LSL}{6\sigma} \quad (42)$$

where USL and LSL define the upper and lower specification limits and σ is the standard deviation [131]. In effect, the capability index is a measure of the variability in the metric of interest. A value of 1 is interpreted as the system is capable of meeting the specified tolerance, or allowable variability. Additionally, the decision-maker wishes to know how far the metric of interest is from the ideal, or target value. This is captured with another capability index, called C_{pk} , and is defined by

$$C_{pk} = C_p \left(1 - \frac{|T - \mu|}{(USL - LSL)/2}\right) \quad (43)$$

where T is the target value and μ is the mean of the associated metric distribution. In spite of the similar semantics of robust methods and technological uncertainties, one difficulty may be encountered. Specifically, most robust design techniques were based on determining robust solutions for manufacturing processes, which typically have very small variability magnitudes on the order of 10^{-6} , and small changes in the mean value. However, the variability and shift in the mean value associated with technological uncertainty is large in magnitude and the standard measures for robustness may fail.

Another assumption that was made in the Technology Evaluation step was that the impact of multiple technologies was additive. However, in the course of applying the TIES method to various systems in the future, a situation might arise where the impact of multiple technologies is *not* additive. One solution to this dilemma would be to introduce

a Technology Compatibility Factor as shown in Figure 81. The original definition of compatibility could be modified to a “fuzzy” scale that would range between “0” (incompatible) and “1” (compatible). Fuzzy logic techniques could be utilized to define the scale of compatibility and then used as a multiplier to the new technology vector element as shown with the non-additive summation of technologies for T1 and T2. Fuzzy logic would be an appropriate technique for defining the extent to which technology combinations are compatible since this would be a subjective evaluation.

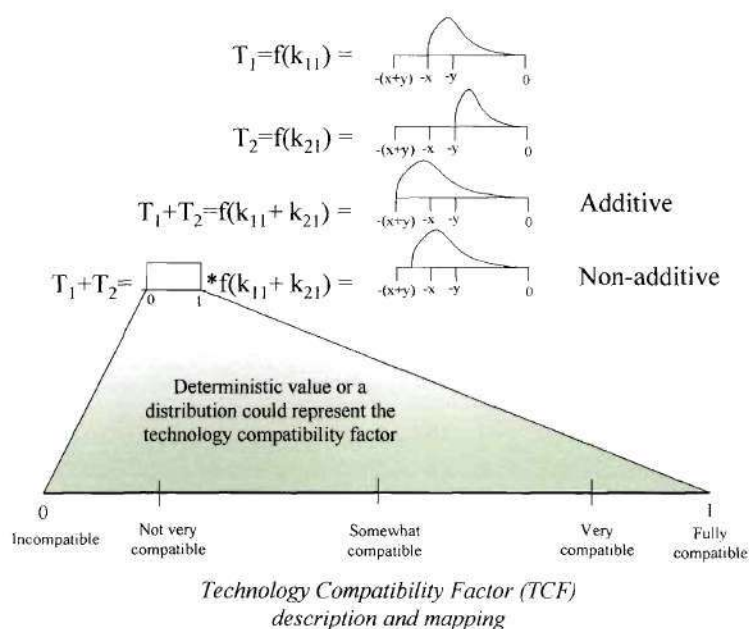


Figure 81: Technology Compatibility Factor

Finally, the most important recommendation of future research efforts should be in the area of quantifying the amount of investment monies needed to develop a technology and the time needed to mature the technology to a TRL of 9. Recall from the technology frontier discussion in Chapter IV, the measure of comparison of the different technology alternatives was chosen to be the Research, Development, Testing and Evaluation

(RDT&E) costs. As reasoned previously, RDT&E was not the best comparison metric for the effectiveness parameters (EPs) due to the dependency on weight. The ideal comparison metric should be the total investment cost associated with developing the technology to maturity. If the EPs were compared to the investment cost, as depicted in Figure 82 for an arbitrary confidence level, the increase in the number of technologies not only increased the effectiveness, but also the investment cost. The *accurate* “ideal” solution would be based on the minimum costs for one technology and the effectiveness parameter of a combination with “n” technologies. This approach would be the most accurate and informative to the decision-maker. In a real development program, the investment cost would be above and beyond the RDT&E and production cost penalties considered herein. Presently, the RDT&E metric was considered the best available economic measure for comparison until a capability to quantify the investment cost can be created. A guideline of how this capability could be created is now discussed.

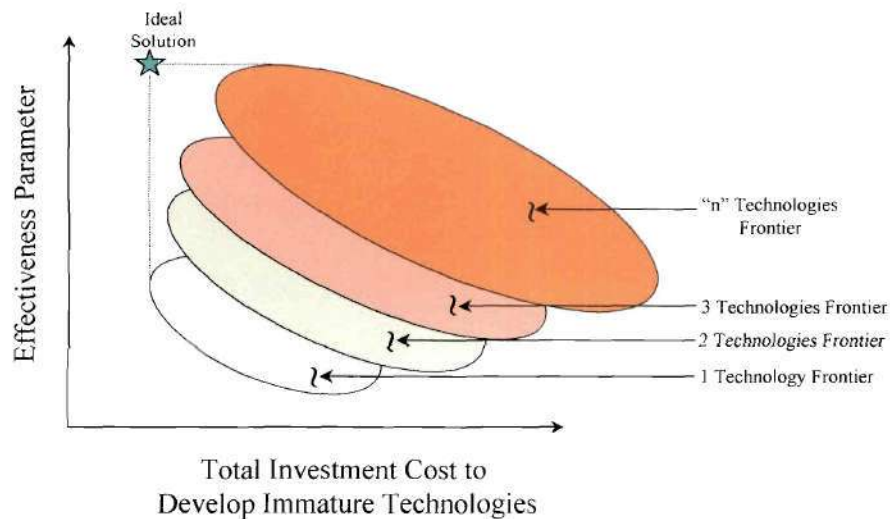


Figure 82: Ideal Effectiveness Parameter Variation with Investment Costs

In a real technology development program, the problem is three-dimensional and is a function of performance (or impacts to the system), cost, and schedule. In this dissertation, only the impacts to the system were considered and the technology was assumed to be ready for implementation when the vehicle went into production. However, to accurately assess a technology, the decision-maker should ask the following:

What can I get from the technology with the R&D money I have and when I need it?

Or, I want this much from the technology. How much will it cost and when can I have it?

Either one of these perspectives would add a new twist to the current TIES method, in that the evaluation would have to become stochastic (time varying probability), rather than just probabilistic. What exactly does that statement imply? Consider how the progress of the technology was defined as a function of program effort in Chapter III, where the constituents of program effort are the resources available and time, as shown in Figure 83. If a technology is successful in meeting the desired performance improvement at a particular date and within budget, one could estimate that the variation in time and resources would vary as shown on the right.

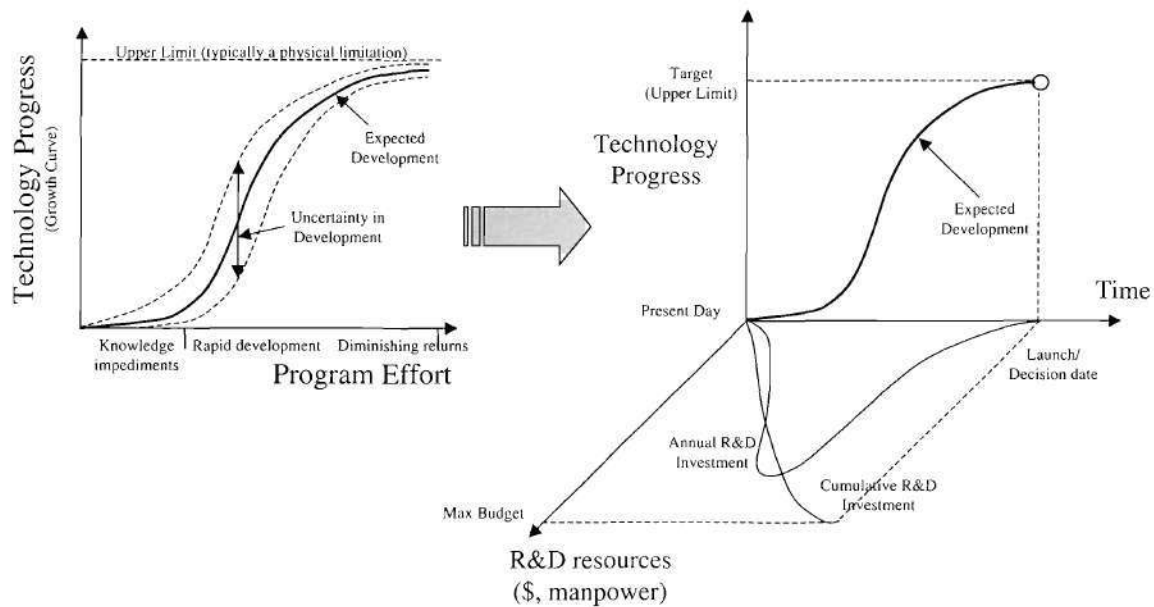


Figure 83: Technology Progress as a Function of Time and R&D Resources

However, all three axes are shown without uncertainty. As with the technological uncertainty, uncertainty exists for the time and resource elements as well. For example, the available R&D budget may deviate annually based on company strategies, loss of markets and profits for extraneous internal R&D, congressional funding cuts, etc. Subsequently, if the funding for the technology deviates from the original development schedule, the launch date will be affected. Likewise, deviations from the original development schedule affect the required resources. In fact, extending a development program increases cost, but accelerating it may also increase costs, such that “once a schedule is established, accelerating it is disruptive, [and] may demand overtime payment to workers, increases the strain on facilities, and exacerbates concurrency risks caused by overlap between development and manufacturing activities. Decelerating the schedule, on the other hand, increases the cumulative effect of fixed costs and introduces inefficiencies associated with operating less than a critical mass.”[132]

The uncertainty introduced for the cost and the schedule complicate the evaluation of the impact of a technology. One technique that shows potential for capturing the three-dimensional uncertainty is a program called the Venture Evaluation and Review Technique (VERT). VERT is a mathematical, modeling and simulation based network technique [133]. This is a well-tested tool for stochastic tree-network modeling and simulation of the “project-environment” dynamics under uncertainty and has the following capabilities [134]:

- 1) analyze extremely complex dynamics of a “venture - external environment” system under uncertainty
- 2) account for time, cost, and performance variables simultaneously
- 3) model system logic relationships as a tree-network of relatively simple activities and events
- 4) account for a range of possible alternatives and uncertainties (“what can happen”, “how likely the outcomes are”, “what will happen if”, etc.)
- 5) assess the risk and success of undertaking a new venture
- 6) monitor, evaluate, and repair on-going and future projects
- 7) estimate the time, cost, and performance values for project outcomes
- 8) identify potential problems and winning areas (critical and optimum paths) based on time, cost, and/or performance criteria
- 9) develop plans to remedy potential problems or explore winning strategies in advance

In fact, based on the above capabilities, a union between the two methods (TIES and VERT) is as natural as vanilla ice cream and warm apple pie. However, the linking of VERT to TIES requires more than a simple linking of analysis tools or techniques, but a detailed investigation of how the readiness of a technology would map to the schedule and monetary requirements. One possible approach to incorporating the VERT program

with TIES is the following. First, based on the Technology Readiness Levels, one could establish specific activities that are required to move from one milestone to the next. This would require the identification of the activities that are associated with a given type of technology. For example, a materials technology would require more finite element modeling and fatigue and static testing, while an aerodynamic technology would require more analysis with a computation fluid dynamics code and wind tunnel tests. Thus, one could establish different classes of technologies and subsequently identify the major tasks associated with developing that technology class.

Once the major activities are identified, the associated costs required to achieve the milestones (or different TRLs) must be determined. One possible source of information for the approximate costs of the activities could be the RDT&E capability within the Aircraft Life Cycle Cost Analysis (ALCCA) program, currently used in the Modeling and Simulation environment of the TIES method. Many of the same activities that are performed in a technology development program are similar, if not identical, to the activities required developing an aircraft system. Thus, one could extract the cost estimating relationships of interest to estimate the technology development activity costs. The most accurate source of information would be to examine existing technologies and the paths and activities that were required for maturity. However, convincing an airframe or engine manufacturer to release company secrets for public consumption is highly unlikely.

Next, one must establish a time to accomplish each activity for a technology class. Acquiring accurate data would again be an arduous task, but could be accomplished through questionnaires to various research entities, such as NASA or academic institutes

that typically perform the various activities. Additionally, the Technology Opportunity Analysis could be used to provide information of how long specific activities are being performed with the bibliometric analysis.

If realistic activities with associated time and costs could be established for the different classes of technologies, the marriage of the VERT program to the TIES method is straightforward. For a given mix of technologies, the VERT network could be analyzed based on the activities associated with that mix of technologies. The anticipated result would be the risk associated with the performance, cost, and schedule axes and could provide the decision-maker more quantifiable data to be used in the Technology Selection step.

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VITA

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